Bio-Inspired Intelligent Sensing Materials for Fly-by-Feel Autonomous Vehicle

MURI Team
Participating Institutions:
Stanford University, University of California at Los Angles,
New York Institute of Technology, University of Colorado at Boulder,
Johns Hopkins University, and University of British Columbia, Canada

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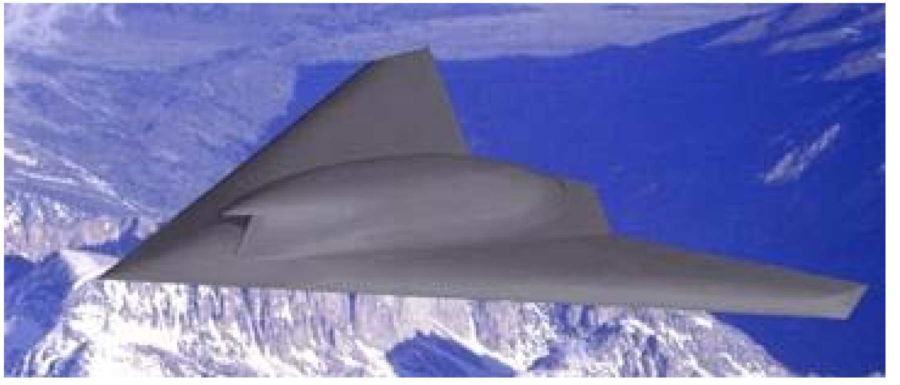
Advantages of UAV



- Lower Cost in Manufacturing
- Reduced Cost in Maintenance and Operation
- Energy Saving for Smaller Size
- Minimal Human Risk

Aircraft Landing in stormy weather

F-15 safely landed with one wing

Fly-By-Feel Autonomous Flight

Sensing

↓

Recognition

↓

State Awareness

↓

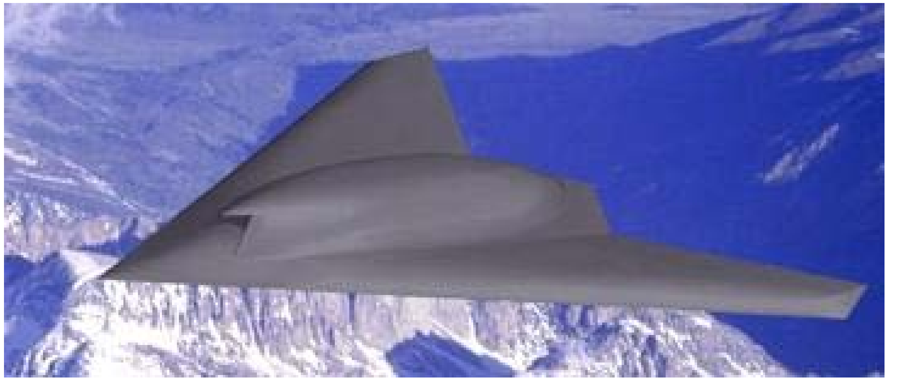
Decision

↓

Autonomous Mode

Essential Steps

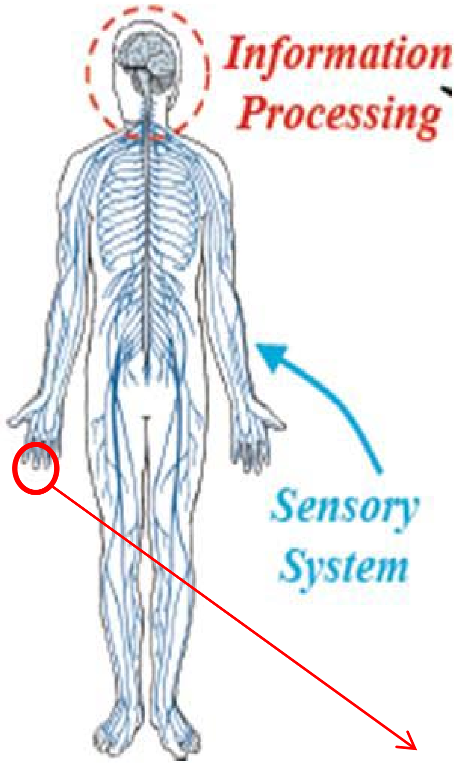
Fly-by-Feel Autonomous Flight



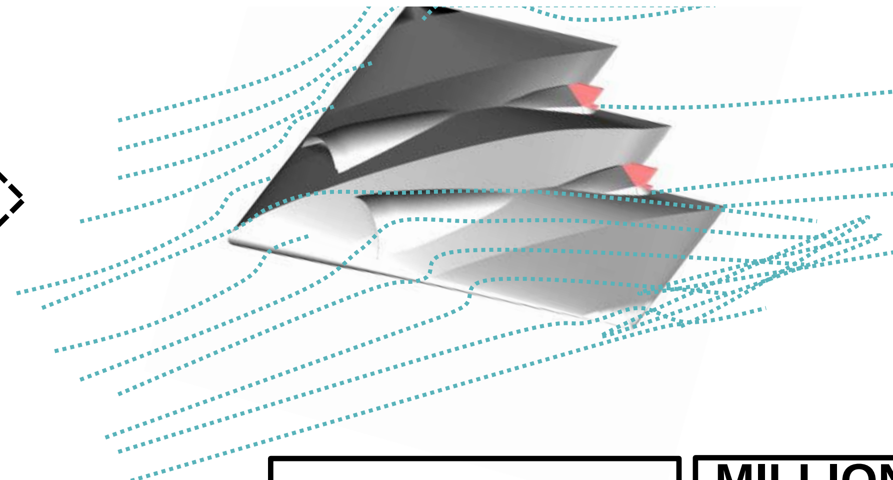
But the system must be:

- •Minimal or no Weight Increase
- •Low Cost in Manufacturing
- •Robust in System Integration
- •Easy for Installation
- •Friendly in Implementation

Bio-inspired Smart Materials/Structures

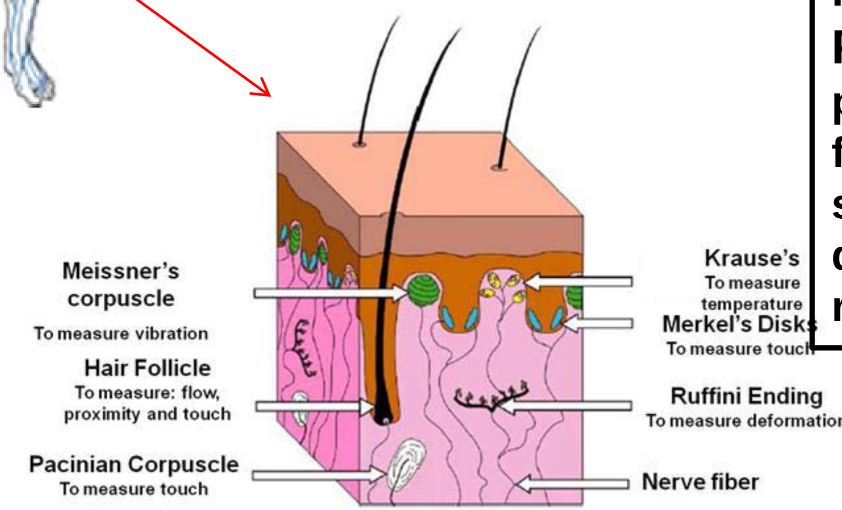


Fly-by-Feel Autonomous Vehicle



Massively Parallel data processing, filtering, self-learning, diagnostics, and real-time decision

MILLIONS of nano/micro-sensors, electronics, processing units etc. over a large area



Bio-inspired Sensory Network

What is an Intelligent Material

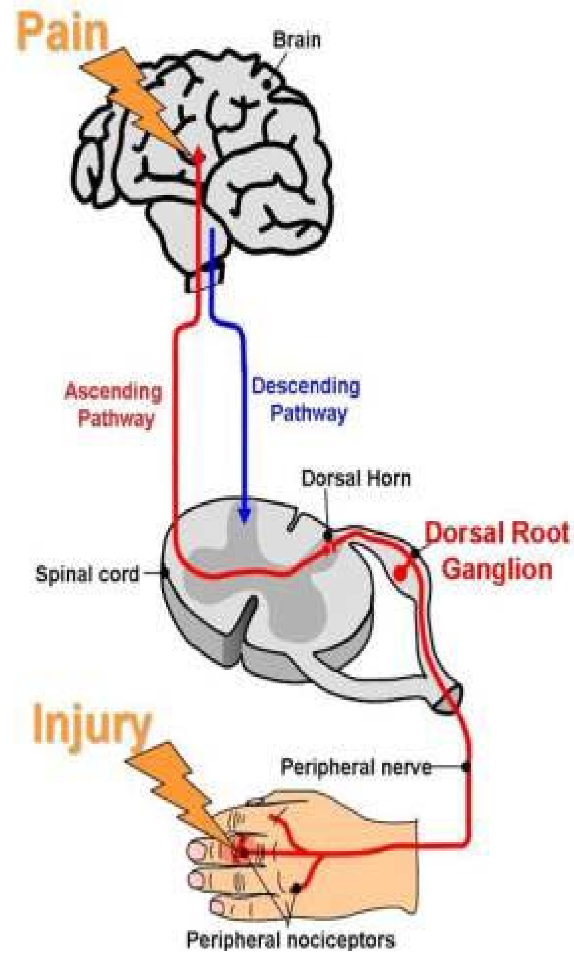
Signals

Materials

Brain
Somatosensory
cortex

Spinal Cord

Nerve
receptors



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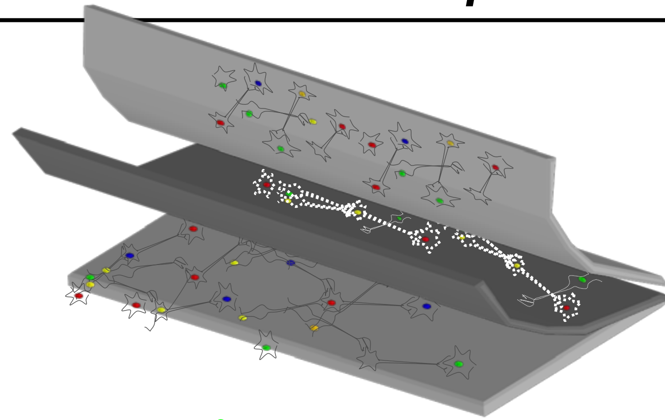
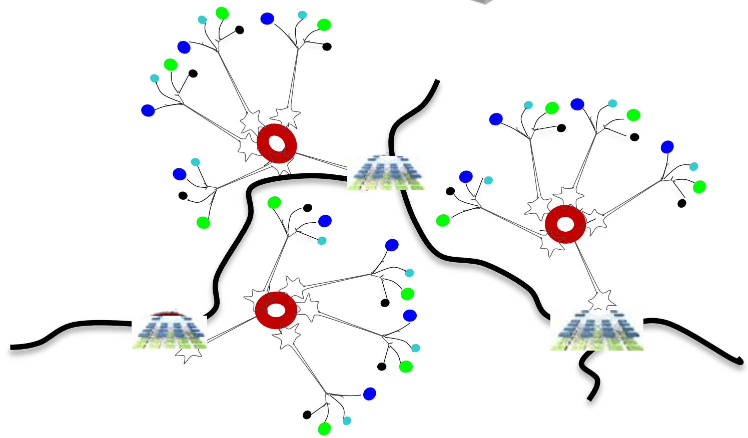
Bio-inspired Sensory Network

Materials Development

Multifunctional Materials

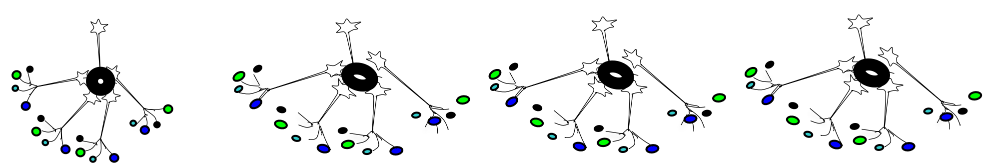


Networks



Processors/Neuron circuits

Multi-functional Sensors

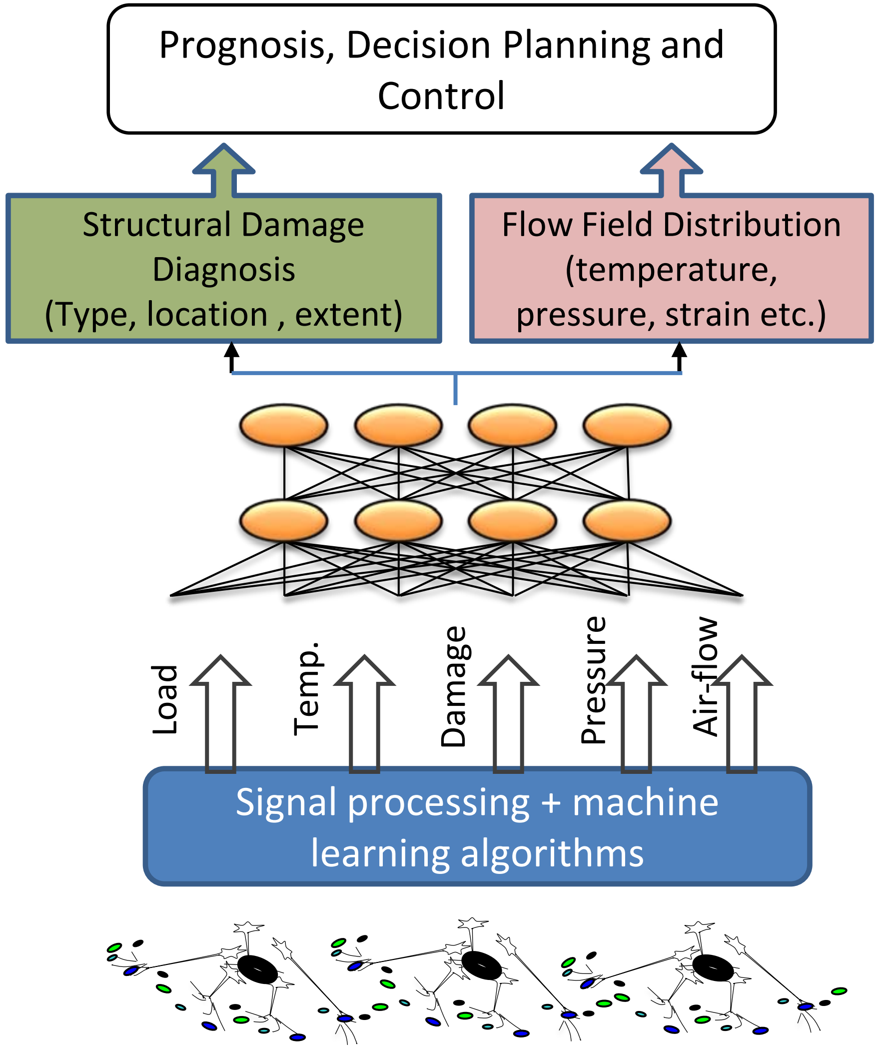


Sensor Processing Development

STAGE 3
Autonomous decision

STAGE 2
State Quantification

STAGE 1
State Classification



Multi-functional Sensors

Research Team

Stanford	Fu-Kuo Chang (PI) – Aero/Astro Boris Murmann – EE Shan Xiang Wang – EE Andrew Ng – CS
UCLA	Yong Chen – ME Greg Carman – ME
NYIT	Rahmat Shoureshi – ME
UC Boulder	Robert McLeod – ECEE
UBC	Frank Ko – ME Peyman Servati – ECEE
JHU	Somnath Ghosh – ME

Major Tasks

- **Bio-inspired Sensor Network**
  - **Stretchable sensor network to accommodate large arrays of sensors and electronics over a large area.**
- **Micro/Nano Sensors for State Sensing**
  - **Multi-physic multi-scale sensors with an ease of network integration.**
- **Neuron Circuits and Interface Electronics**
  - **Bio-inspired neuron circuits with appropriate electronics to interface with various sensors.**
- **Modeling, Design, and Prognostics**
  - **Multi-physic and multi-scale modeling of multifunctional materials with distributed sensing capabilities for design and validation.**
- **Diagnostics and State Awareness**
  - **Embedded intelligent software, Algorithms, tools, and processes to determine the state of the materials in real time.**
- **Integration**
  - **An effort to develop a prototype of "intelligent sensing material."**

Bio-inspired Sensory Network

Chang, Peumans/Wang – Stanford

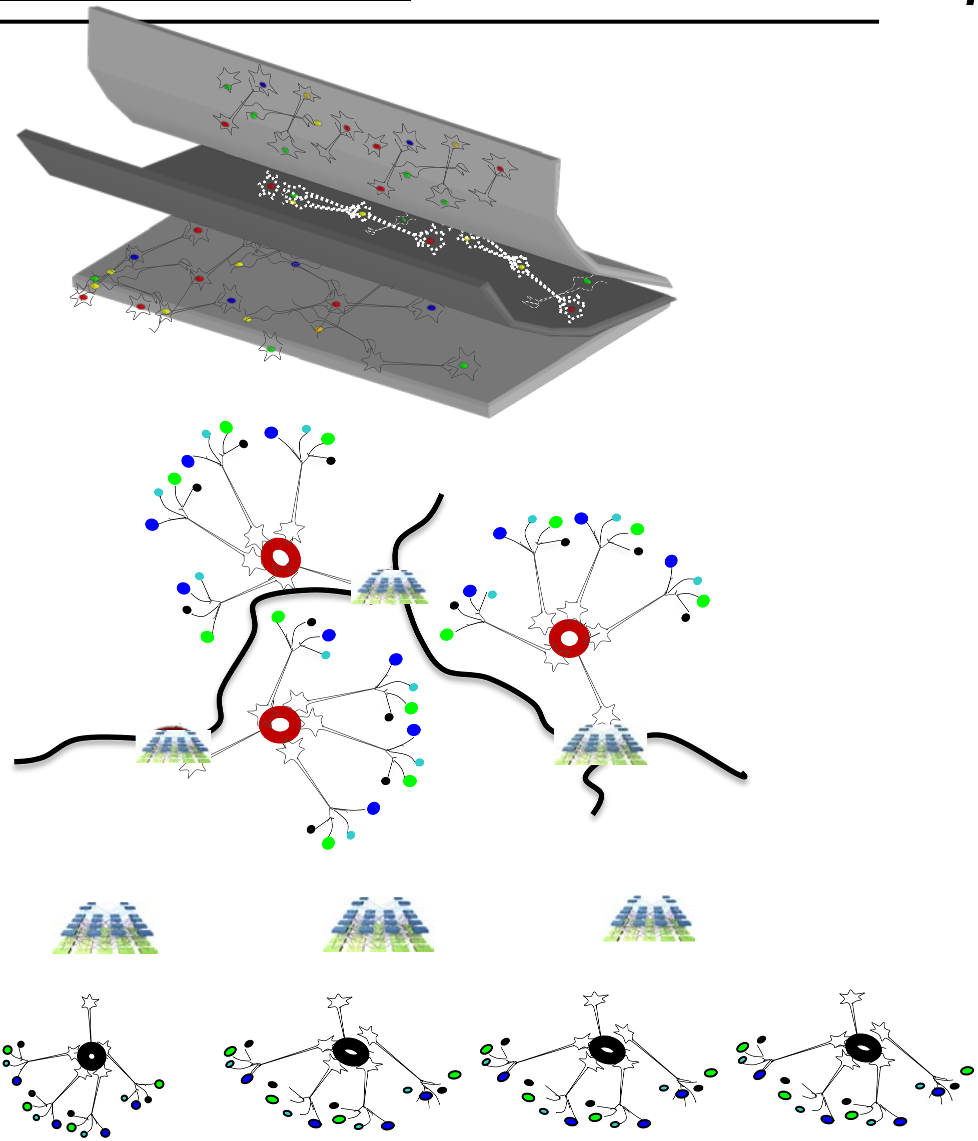
Robust and Low Cost *Materials Development*

Multifunctional Materials

Networks

Processors/Neuron circuits

Multi-functional Sensors



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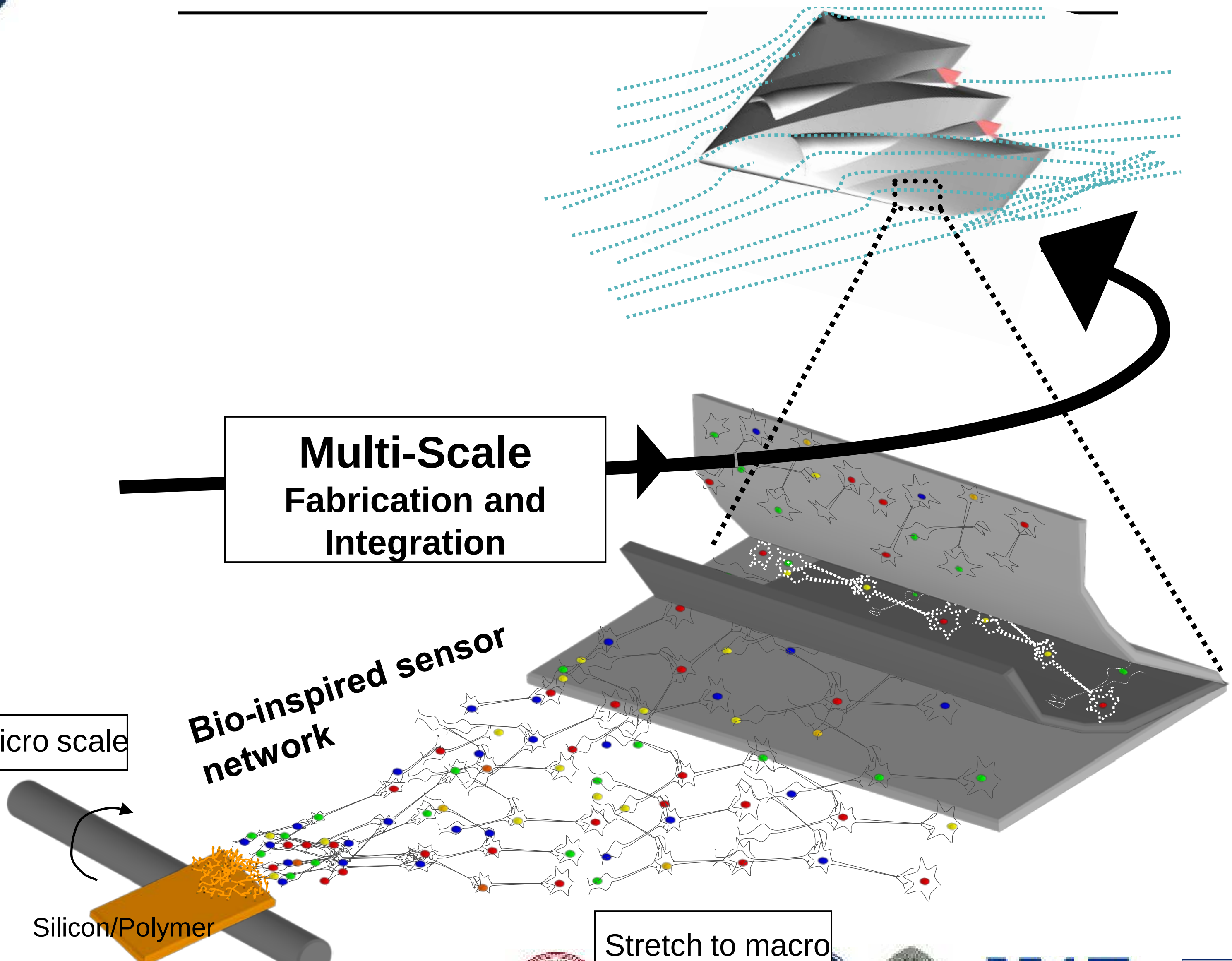
Micro Fabrication for Macro Application



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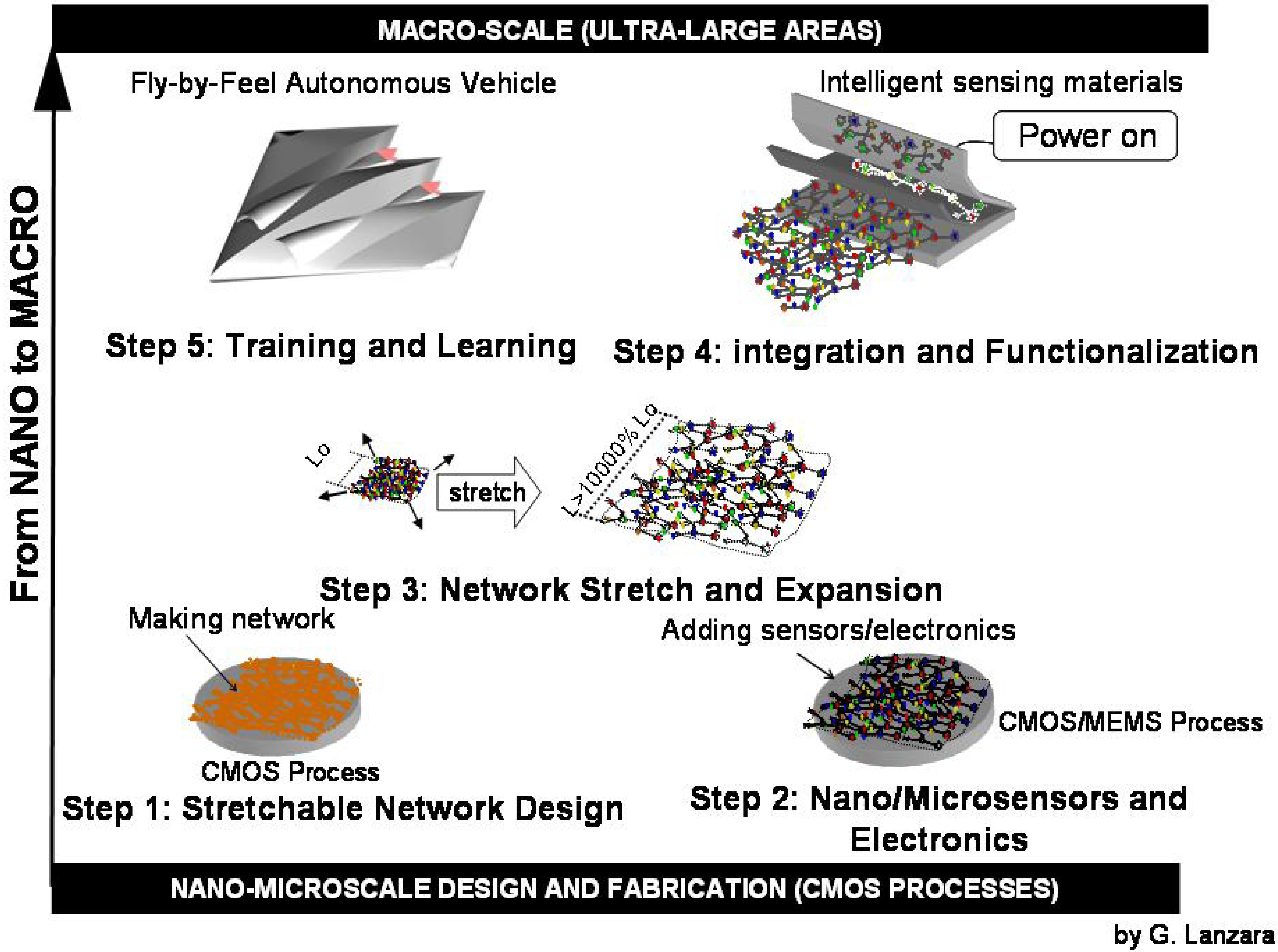
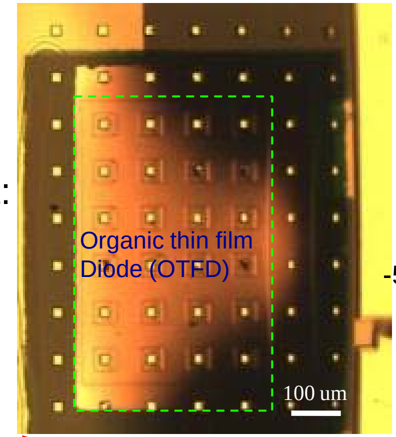

MACRO-SCALE (ULTRA-LARGE AREAS)
From NANO to MACRO
Fly-by-Feel Autonomous Vehicle
Intelligent sensing materials
Power on
Step 5: Training and Learning
Step 4: integration and Functionalization
Lo
stretch
L>10000% Lo
Step 3: Network Stretch and Expansion
Making network
Adding sensors/electronics
CMOS/MEMS Process
CMOS Process
Step 1: Stretchable Network Design
Step 2: Nano/Microsensors and Electronics
NANO-MICROSCALE DESIGN AND FABRICATION (CMOS PROCESSES)
by G. Lanzara

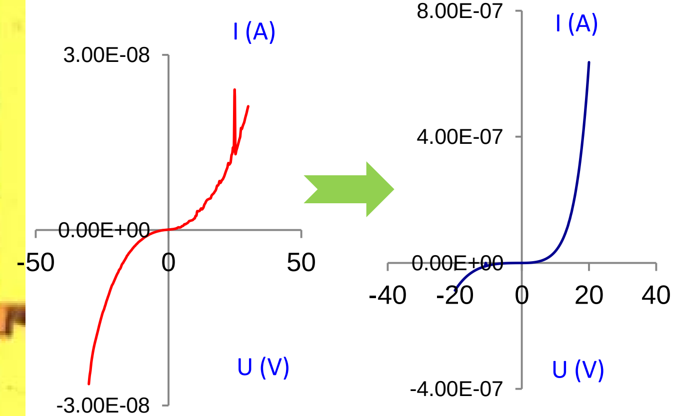
OTFD Sensors for Stretchable Network

- Integration of Organic Thin Film Diodes (OTFDS)
  - Packaged OTFDs in the network
    - Improved diode performance
    - Protect OTFDs in harsh environment:
      - High temperature(350°C),
      - Solvents, acids
  - To measure temperature



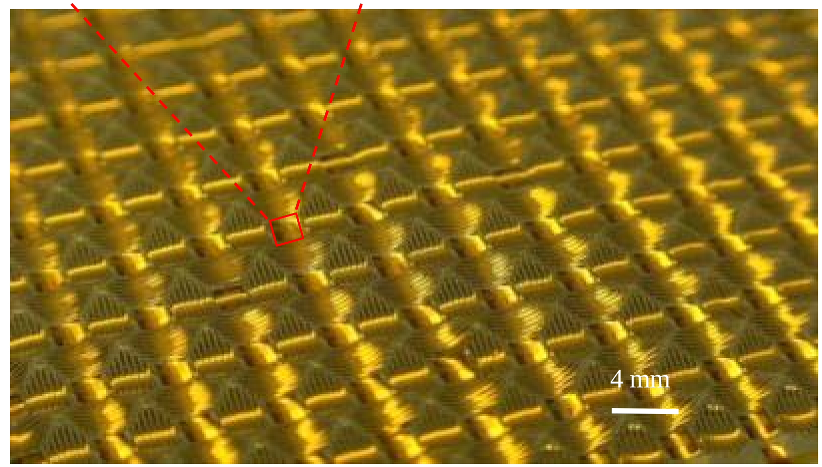
Network node

Organic thin film diode I~V curves (Improved diode performance)

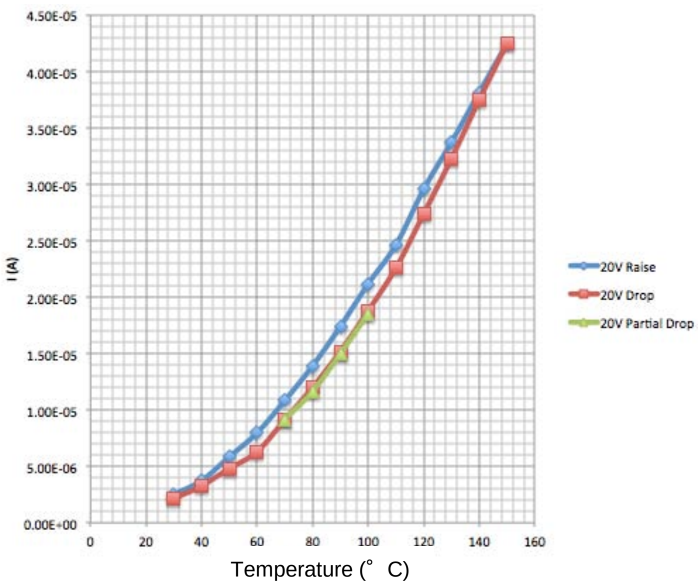


Degraded I~V (2011)

Improved I~V (2012)

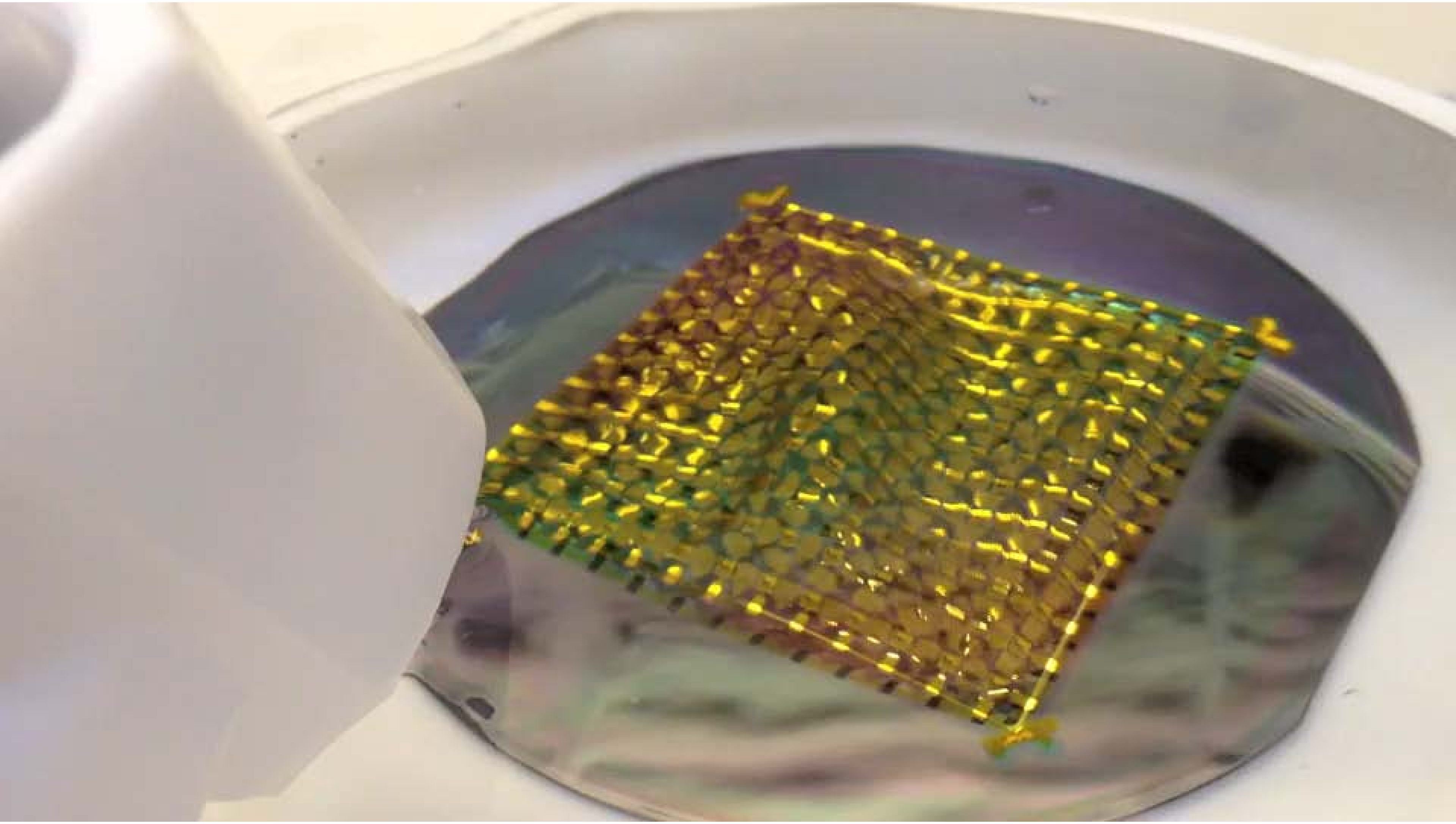


An OTFD based temperature sensor network



Temperature measurement (I~T) of an OTFD

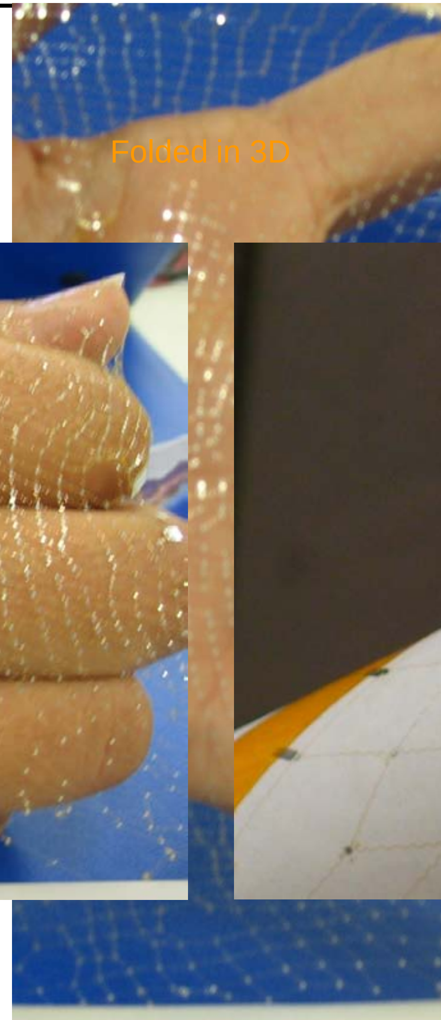
Video:169 nodes network after release

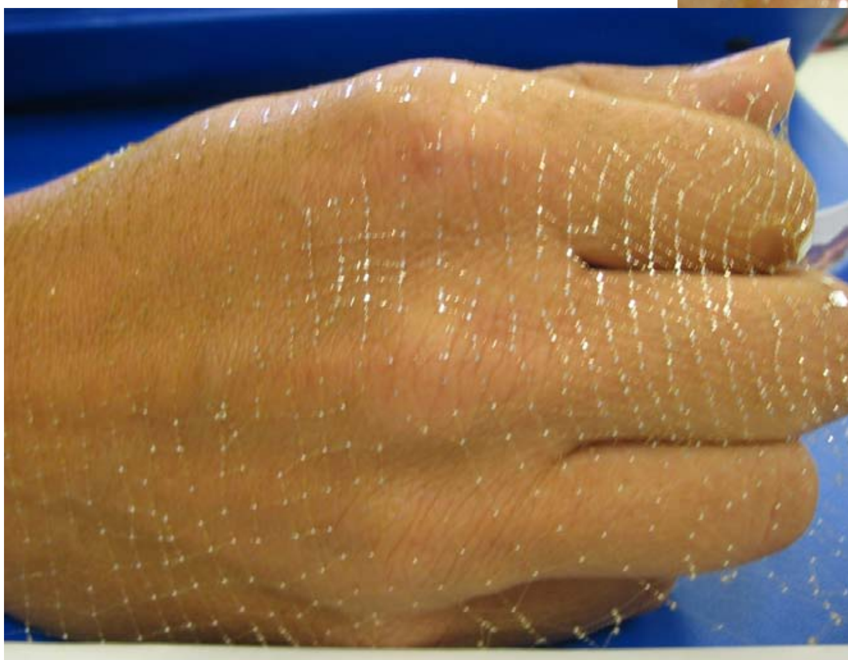


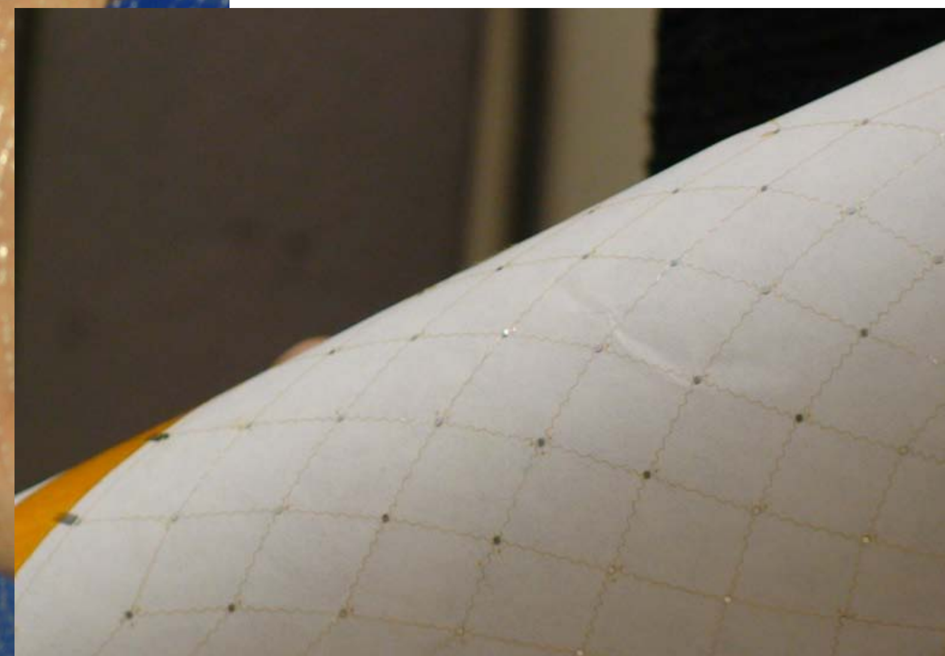
Coating 3D bodies

Expanded network

Folded in 3D







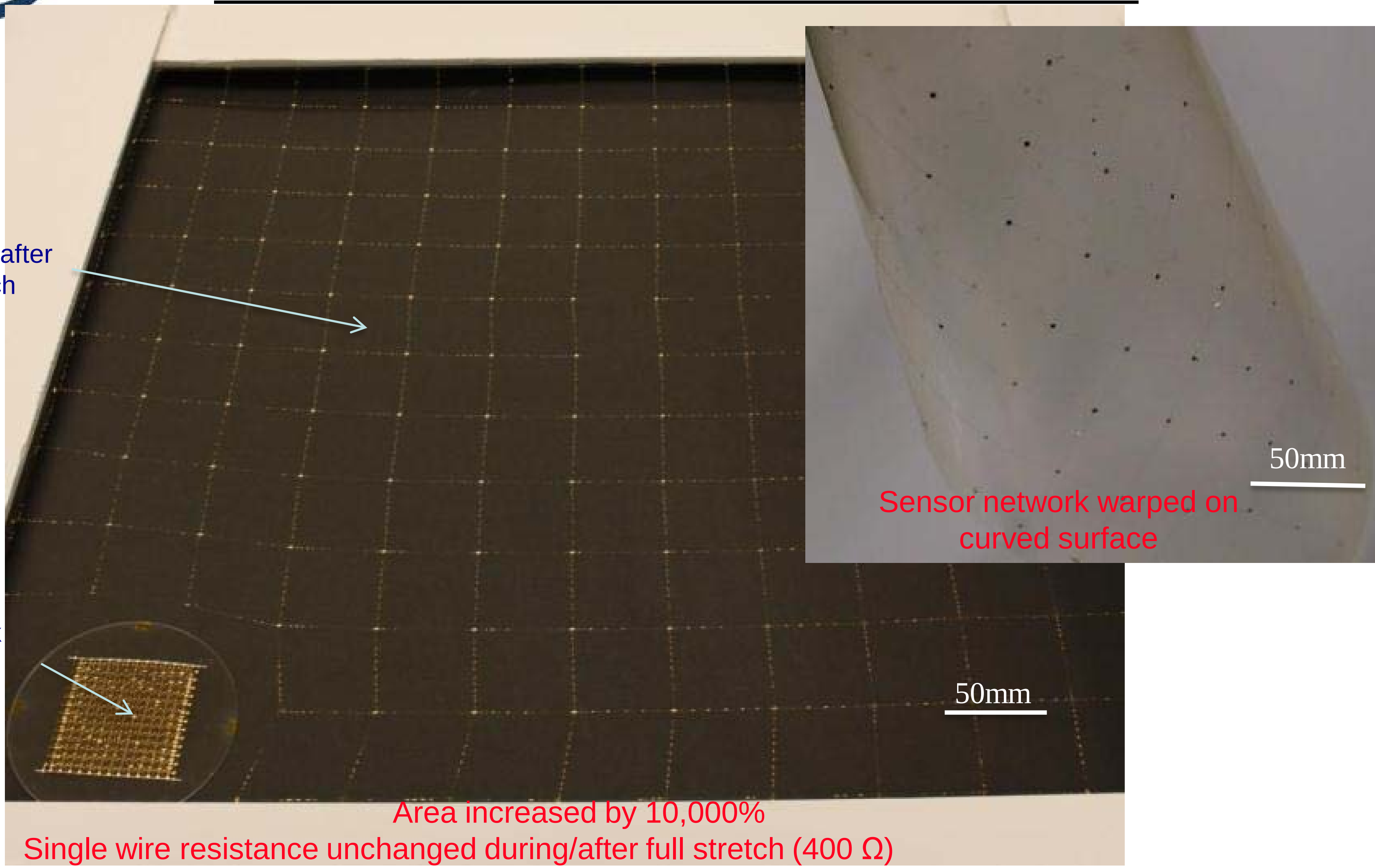
G.Lanzara, J. Feng and F.K.Chang, Smart Materials and Structures, 19, 045013, 2010

G.Lanzara et al, Advanced Materials, 2010

Fully Stretched Sensory Network

Network after full stretch

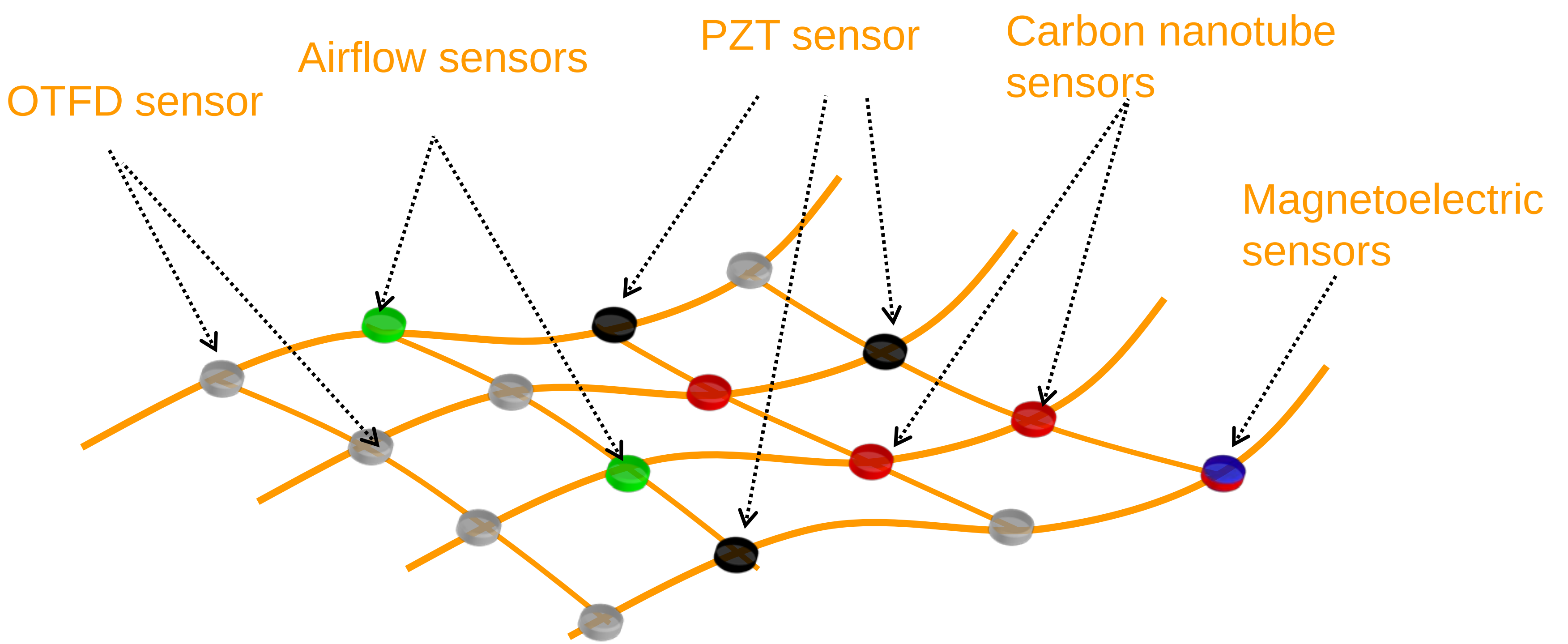
Network before stretch



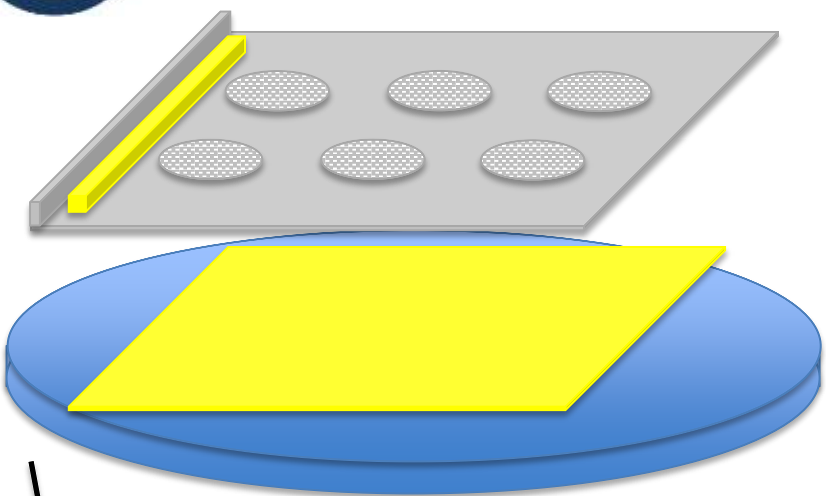
Multi-physic and Multi-scale Sensors

Chang, Wang – Stanford
McLeod – UC Boulder
Carman – UCLA
Servati, Ko – UBC

Network Functionalization



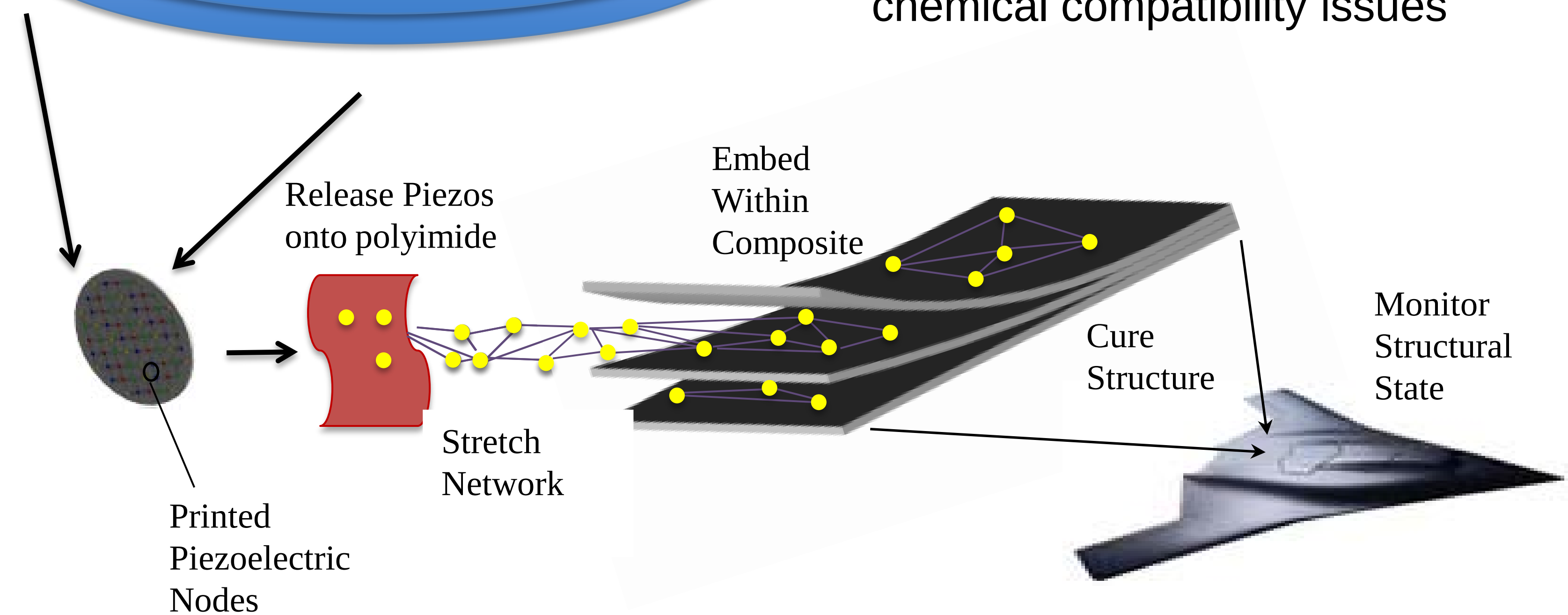
PZT Actuators/Sensors for Stretchable Network



Create piezoelectric sensing systems on the stretchable network

Method: Integrate thick film ceramics into C-MOS processing

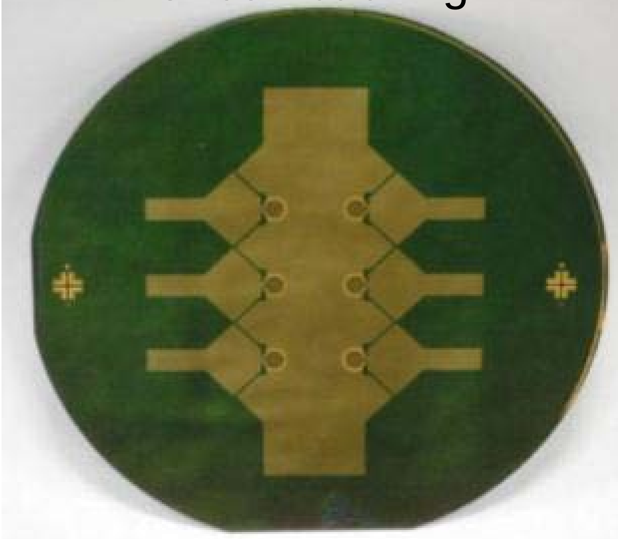
Challenges: Temperature & chemical compatibility issues



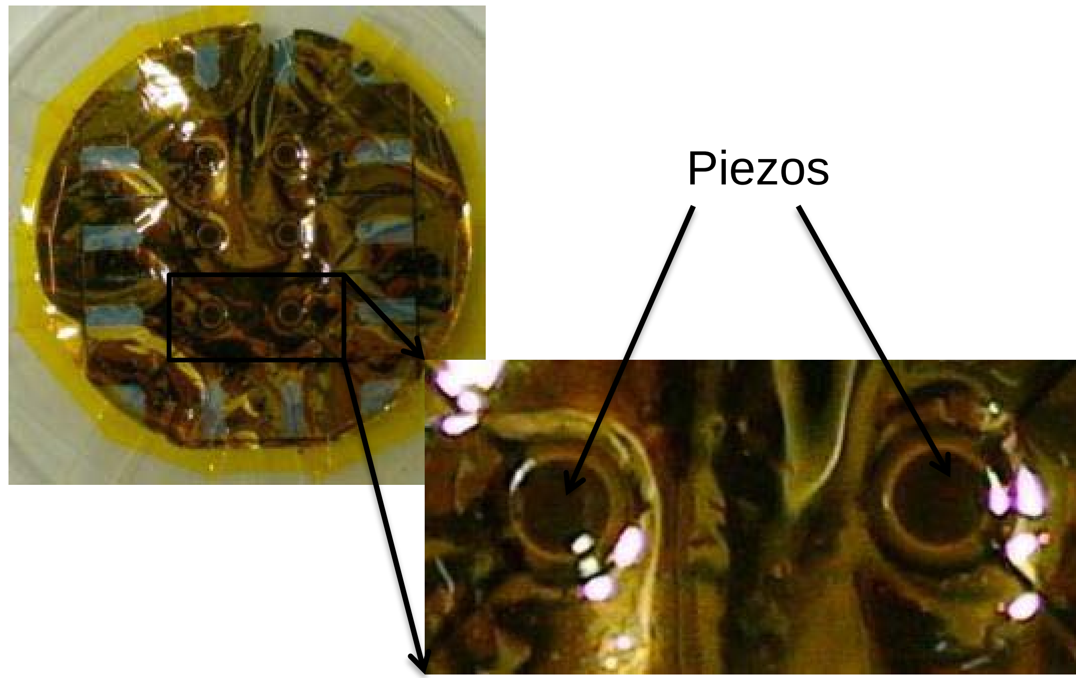
Recent Accomplishments

- Screen printed piezo-ceramics integrated into C-Mos type processing & released onto a polyimide film with electrodes.

Thick film piezos on a silicon backing



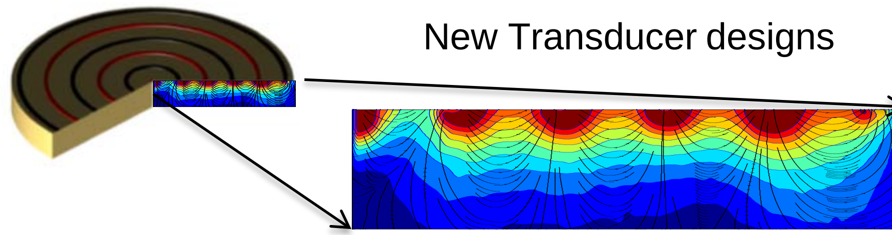
Piezos released onto a polyimide film

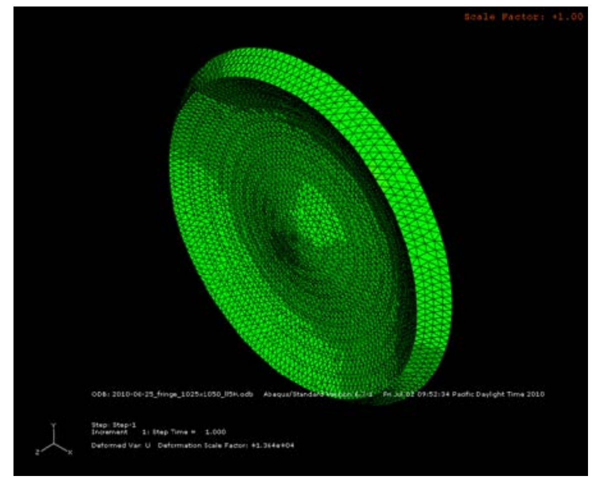


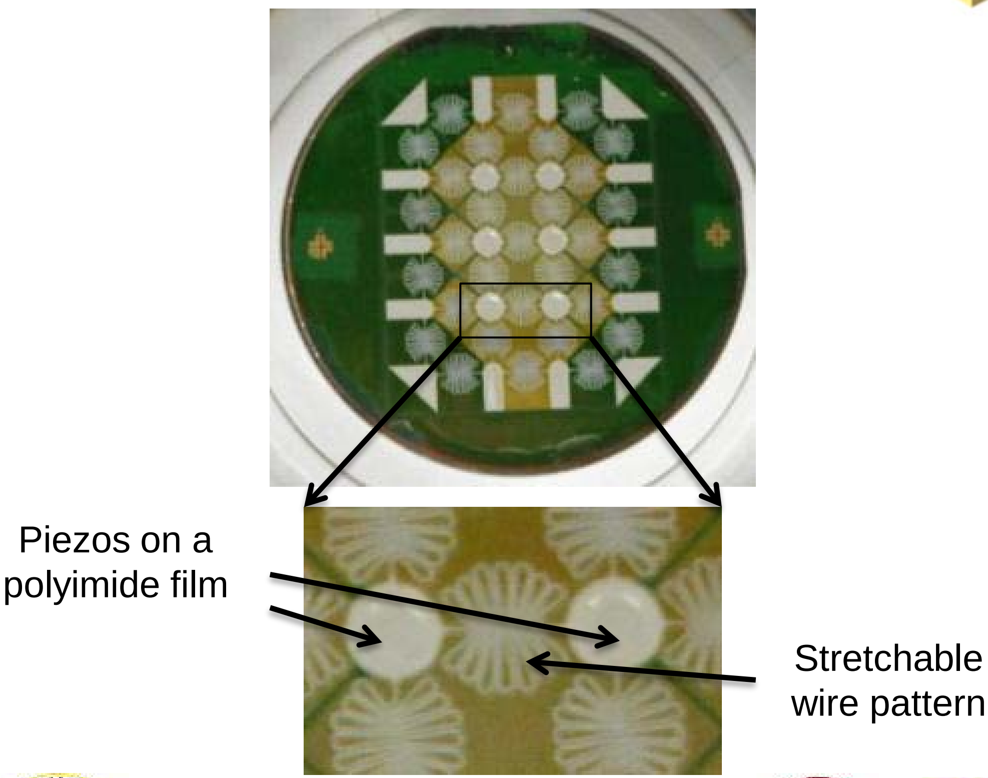
- Innovations
  – New method to transfer piezos from a fabrication substrate to an organic substrate

Ongoing Work

- Create a stretchable network from the screen printed piezos released onto an organic backing
- Characterization of materials
- New transducer designs







Air Flow Sensor Configuration

(Yue Guo, Prof. Shan X. Wang)

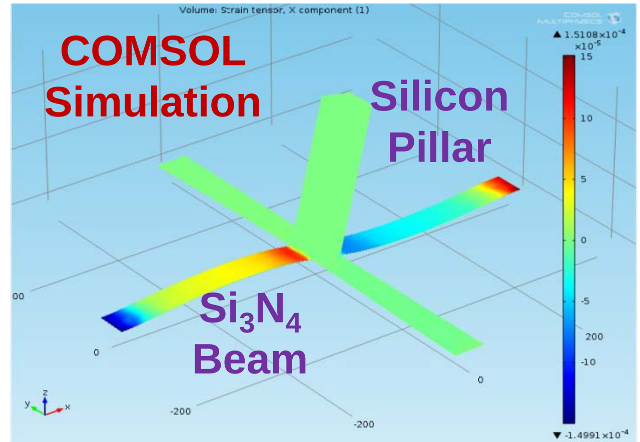
- **Aim:** Obtain the real-time air flow profile (velocity + direction) surrounding the entire airplane

1. **Air Flow hits the pillar**
2. **Deflection in the beam**
3. **Strain in the sensing elements**
4. **Inverse Magnetostrictive Effect**
   Stress → Magnetization rotation
   → Resistivity change, ΔR/R

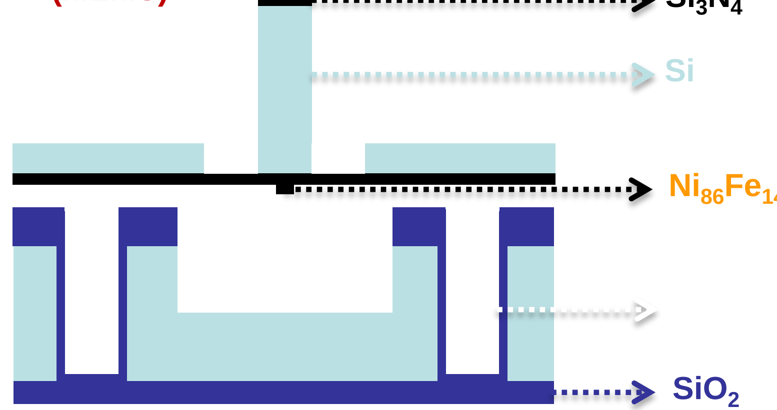
   Or Piezoresistive Effect
5. **Voltage change from ΔR/R**

Pillar	Values
Length	50 um
Width	50 um
Height	250 um

Beam	Values
Length	350 um
Width	52 um
Thickness	1 um

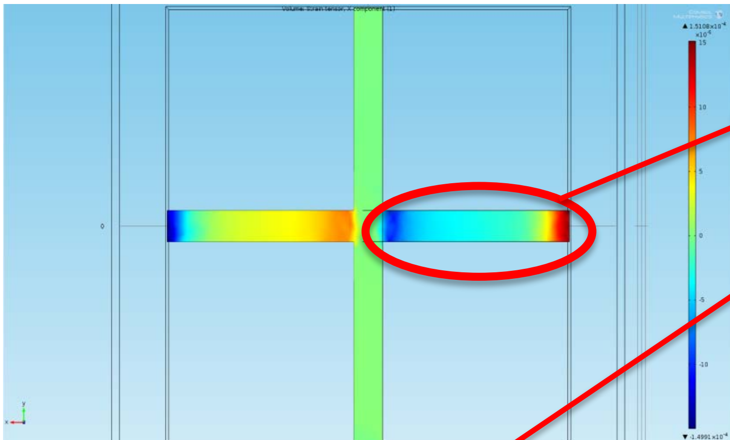


Cross-section View (MEMS)

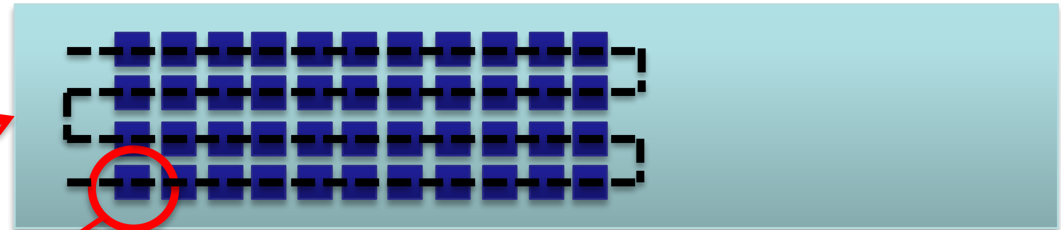


Magnetoresistance (MR) Air Flow Sensor

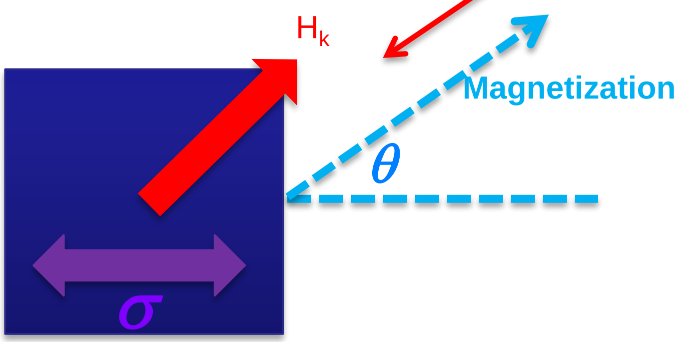
Bottom View of Beams



$Ni_{86}Fe_{14}$ Sensing Elements



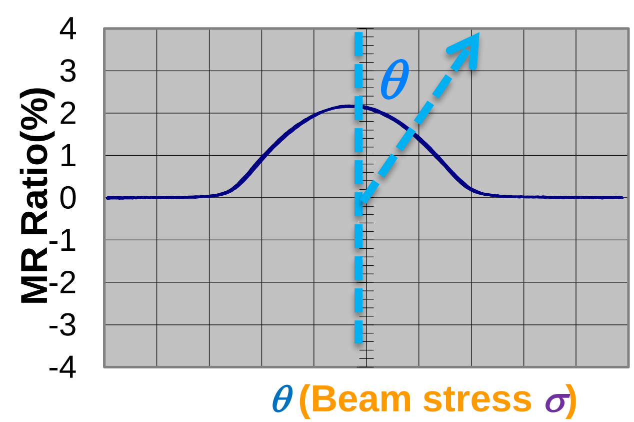
- 4 x10 array in series for larger output signal
- Square shape for avoiding demagnetizing field



stress

$$H_k \sin\left(\theta - \frac{\pi}{4}\right)\cos\left(\theta - \frac{\pi}{4}\right) + \frac{3\lambda_s \sigma}{\mu_0 M_s} \sin\theta \cos\theta = 0$$

MR signal is related to beam stress and thus air flow velocity.



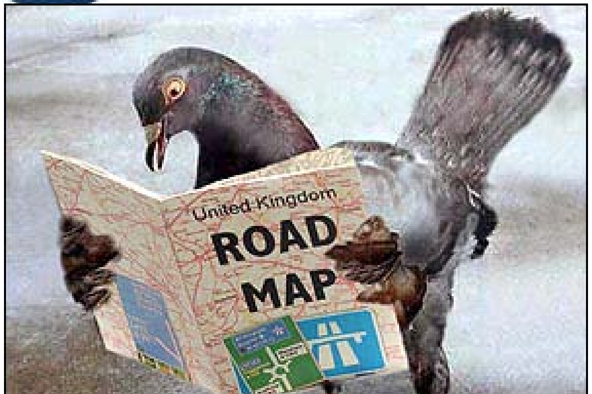
Design Comparison

Sensing Elements	L_{sensor}	W_{sensor}	t_{sensor}
Magneto-resistance	4um x10	4um x4	25nm
Piezo-resistance	50um	25um	40nm

Strain 1e-5	Magneto-resistance	Piezo-resistance
Power	1 mW	1 mW
Resistivity	15e-8 ohm·m ($Ni_{84}Fe_{16}$)	2e-5 ohm·m (PolySi)
Resistance	240 ohm	1000 hm
Voltage & Current	0.5 V, 2 mA	1 V, 1 mA
Current Density	2e10 A/m^2	1e9 A/m^2
Resistance Change	0.11 % (AMR), 0.44 % (GMR)	0.029 %
Voltage Change	0.55 mV (AMR), 2.2 mV (GMR)	0.29 mV
Johnson Noise	2 nV/$\sqrt{\mathrm{Hz}}$	4 nV/$\sqrt{\mathrm{Hz}}$

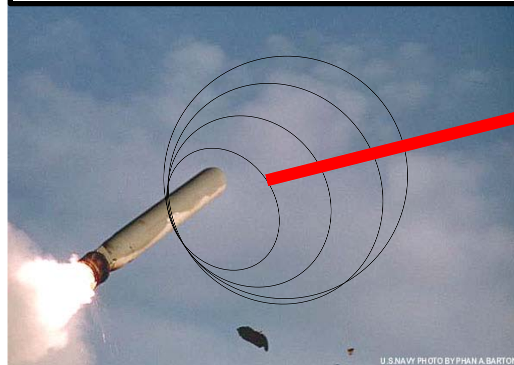
Anisotropic magnetoresistive (AMR) and giant magnetoresistive (GMR) air flow sensors with 1 mW power consumption are feasible and outperform similar piezoresistive air flow sensors.

Magnetoelectric Sensors for Detecting Magnetic Field (Carman's Group)

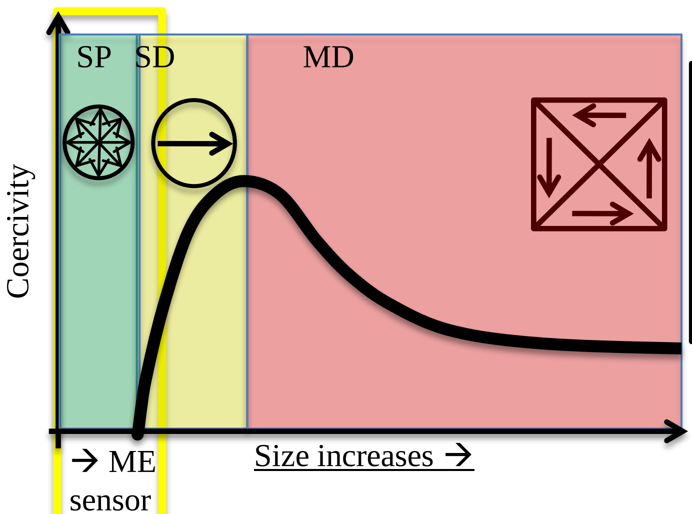


Beak and/or visual cortex contains superparamagnetic particles to track/see magnetic flux lines

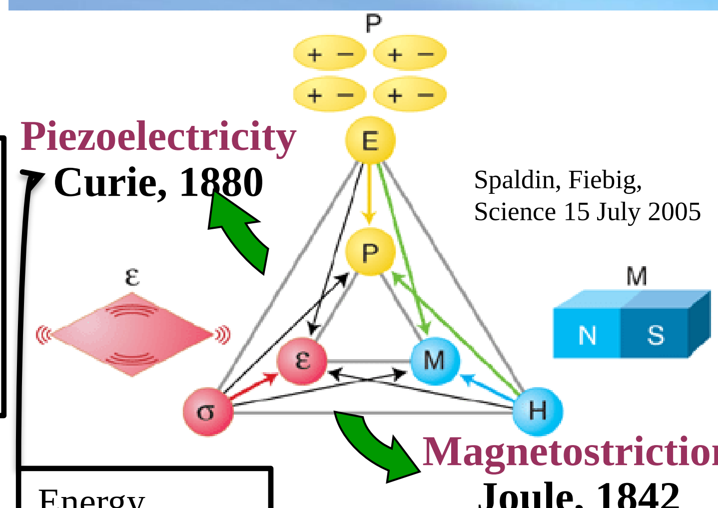
Detecting incoming threats using magnetic perturbation



http://www.usswisconsin.org/



Develop sensitive magnetometer using biological inspiration & phenomena present only at nanoscale



Spaldin, Fiebig, Science 15 July 2005

Energy Transduction

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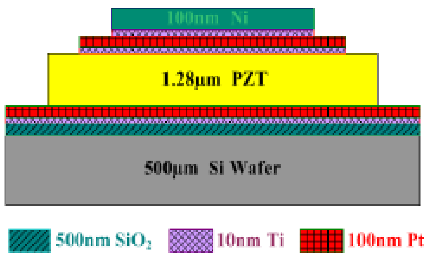
NYIT New York Institute of Technology

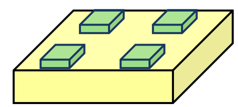
UBC

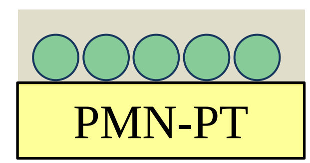
Method of Approach

Nanoscale Magnetoelectric Materials for Detecting Magnetic Fields

2001 – Giant magnetoelectric in bulk composite (Ryu)	> 1000 papers
2004 – Magnetoelectric in thin film	> 50
2007 – Magnetoelectric in SD (UCB and UCLA)	> 5
2011 – Magnetoelectric in SP (UCLA)	~ 0



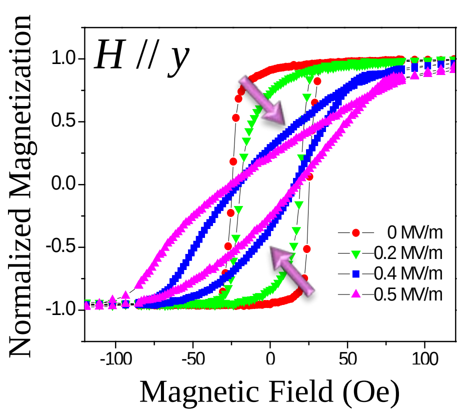


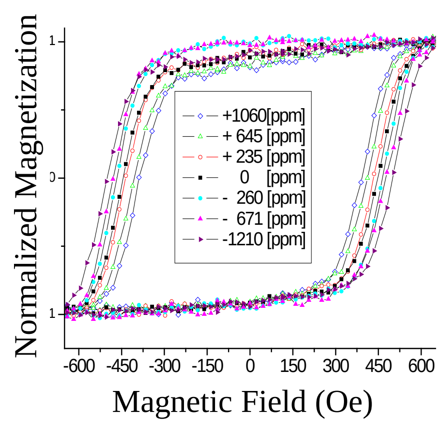


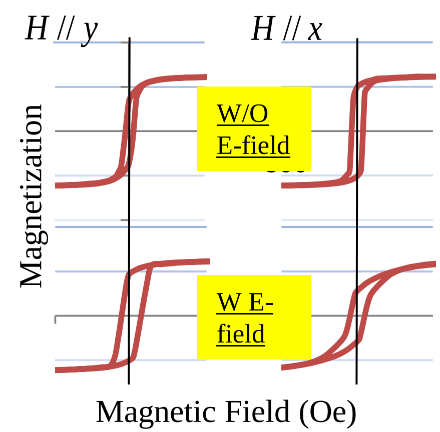
Thin film

Single domain

Superparamagnetic







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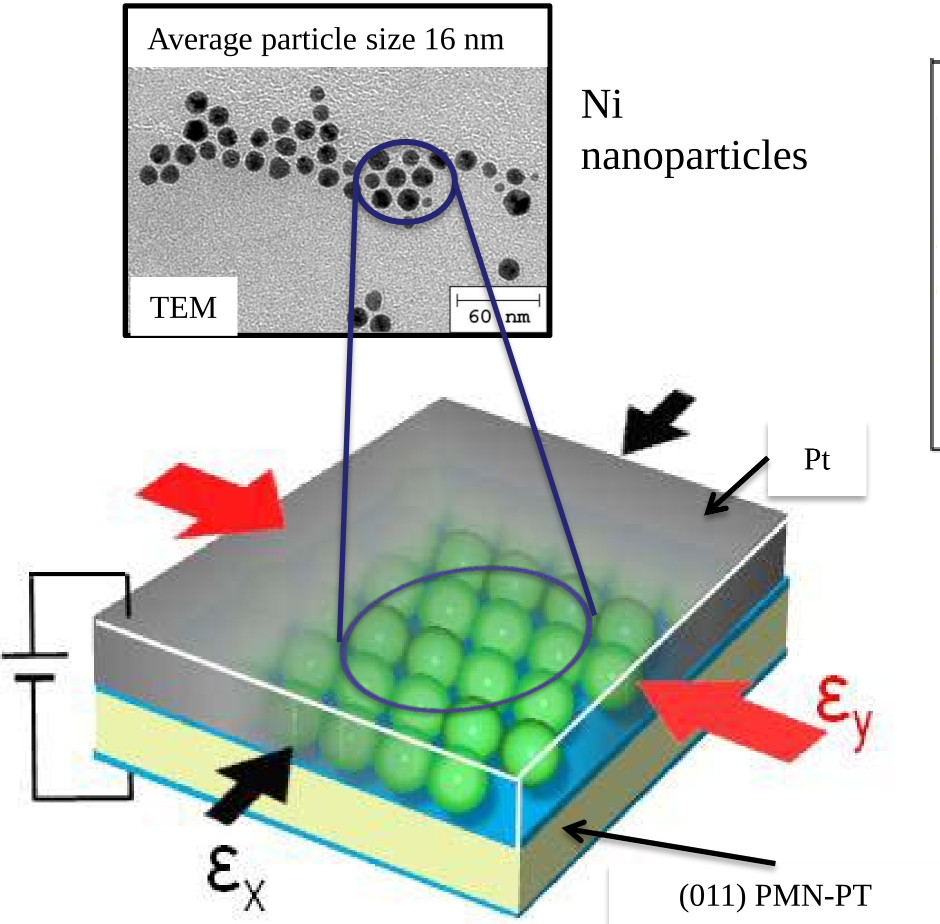
Method of Approach

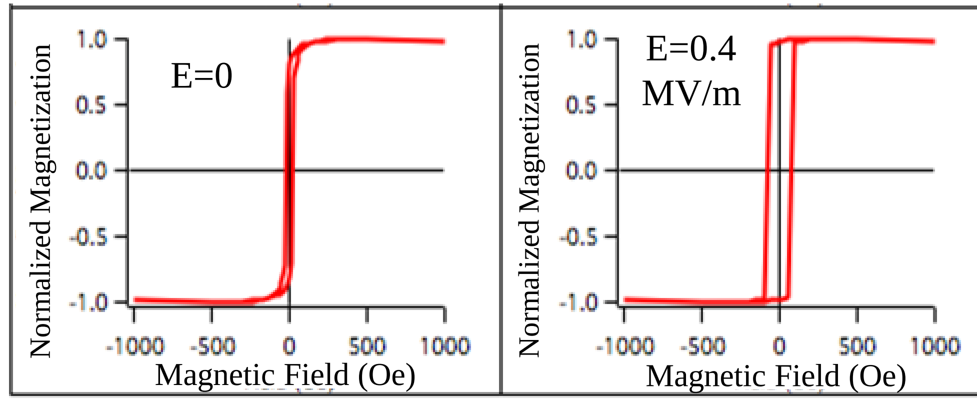
Magnetoelectric Control of Superparamagnetism

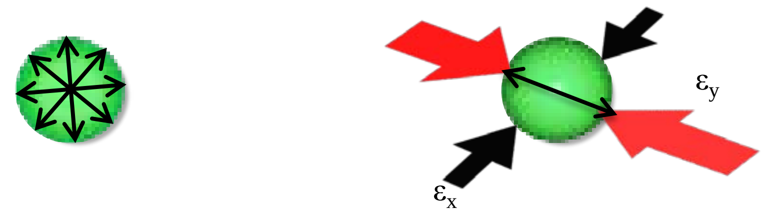


Magnetoelectric composite

Superparamagnetic

Single Domain





- Magnetoelectric composite induces strain in Ni nanoparticles
- E=0 produces superparamagnetic behavior
- E=0.4 MV/m produces single domain structure

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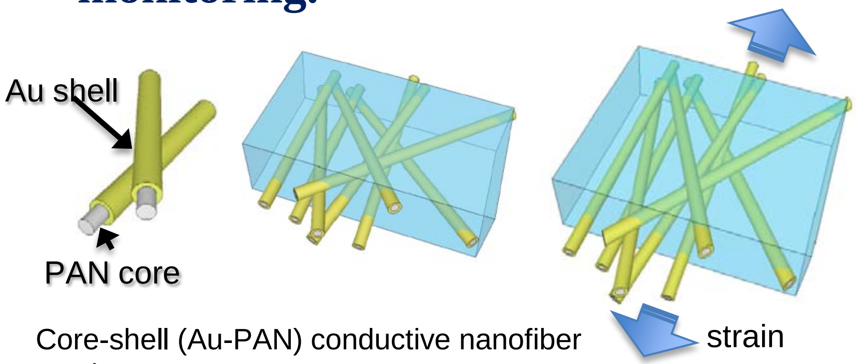
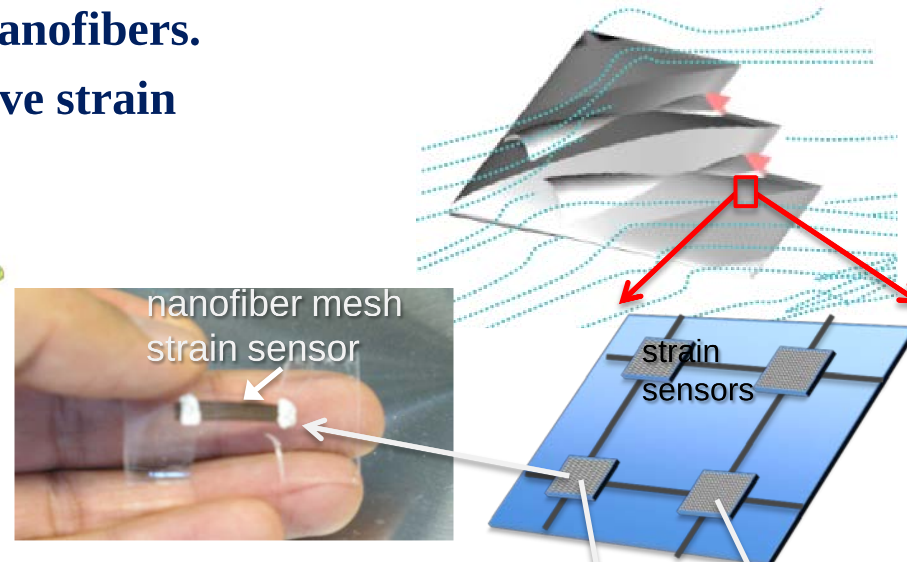
New York Institute of Technology

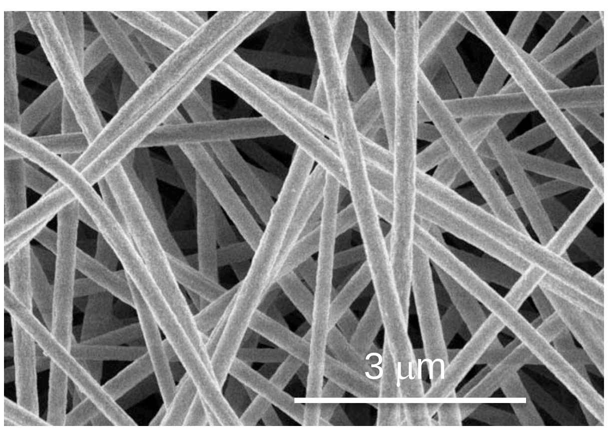
Nano-Strain Sensors (Servati & Ko's Group)

- **Strain sensors based on electrospun nanofibers.**
- **Core-shell nanofibers for ultra-sensitive strain monitoring.**

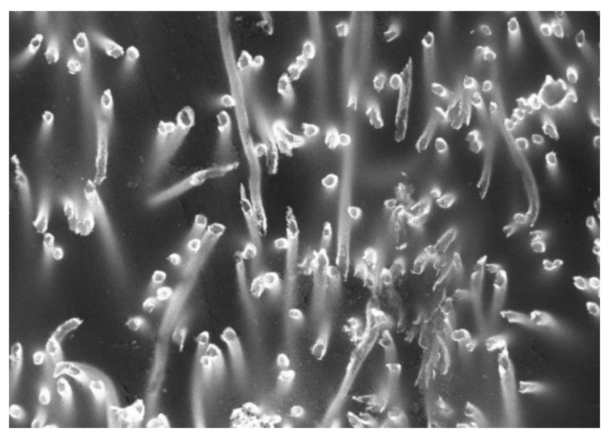


Core-shell (Au-PAN) conductive nanofiber mesh.

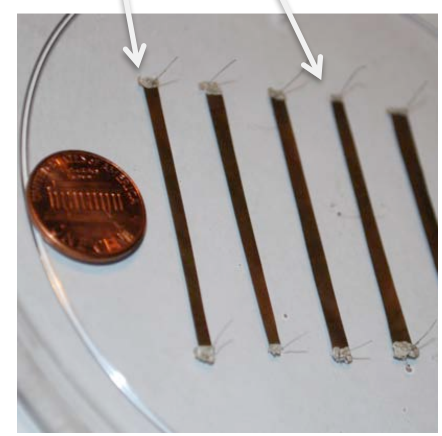




SEM photomicrograph of core-shell (Au-PAN) conductive nanofiber mesh.



Cross section of core-shell (Au-PAN) nanofiber mesh in PDMS.



Several parallel nanofiber strain sensors embedded in PDMS.

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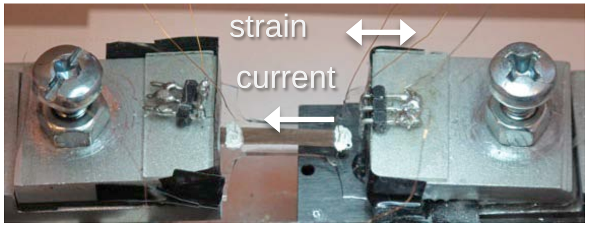
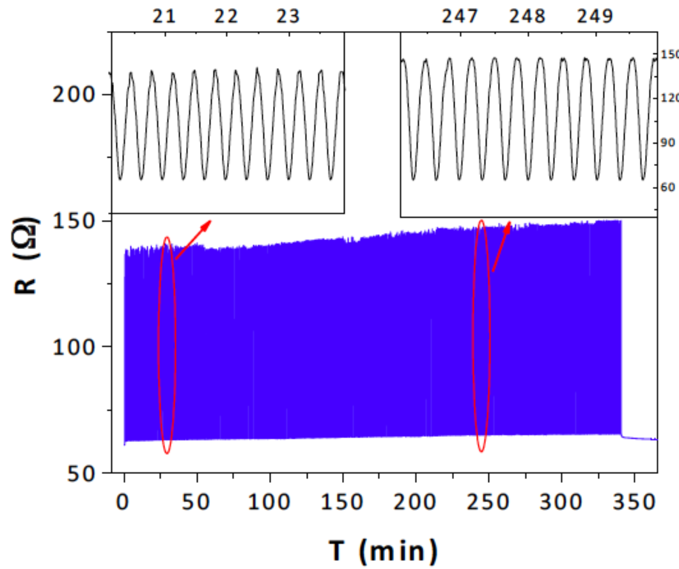
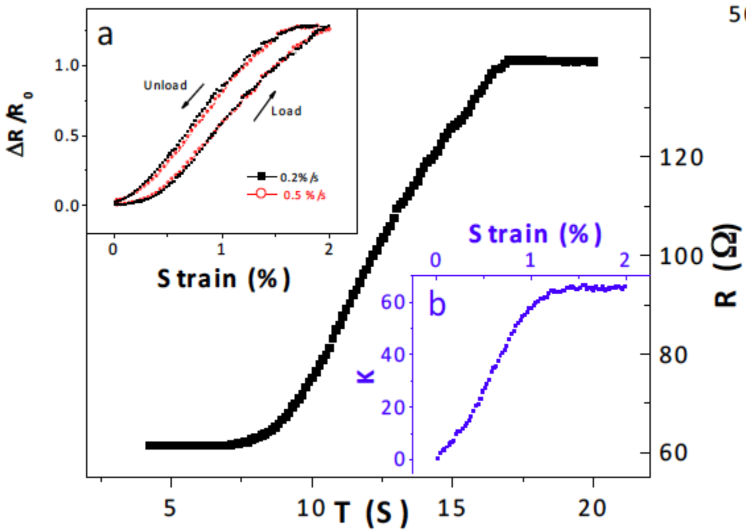
Accomplishments: Stable, High-Sensitivity Response for Planar Strain and Vibrational Monitoring

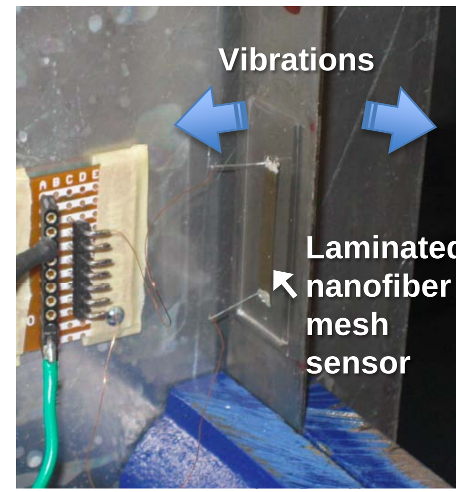




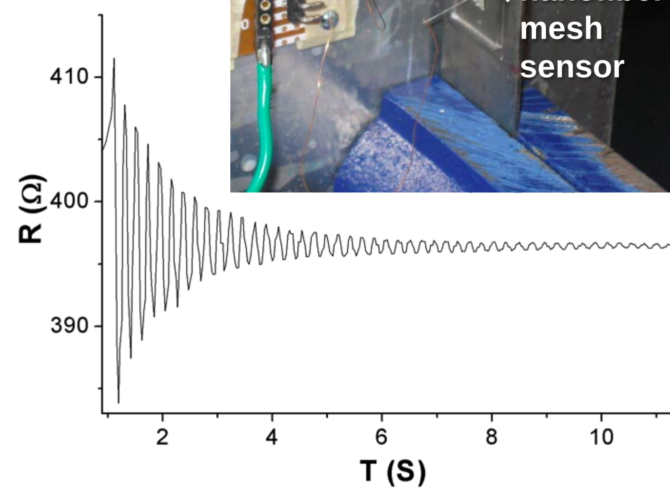
Stable change in resistance over 1000 repeated stretching and unloading of the sensor.



Change in resistance and gauge factor *K* under uniaxial tensile strain.

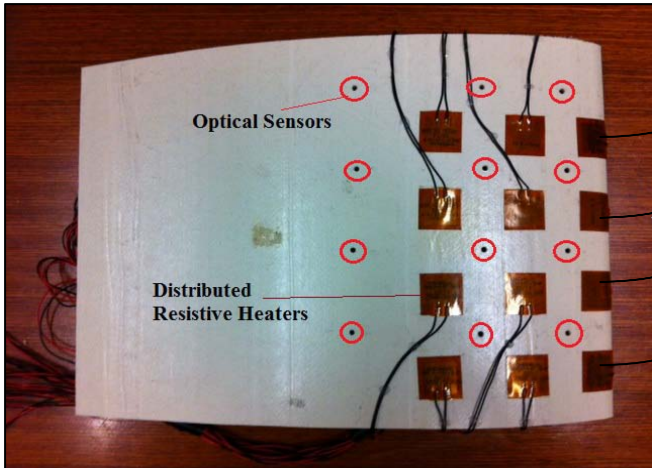


Measured changes in resistance due to vibrations of a rigid metallic blade, showing both **tensile** and **compressive** strain sensing response.

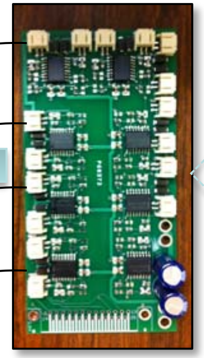


Data flow and CU program overview

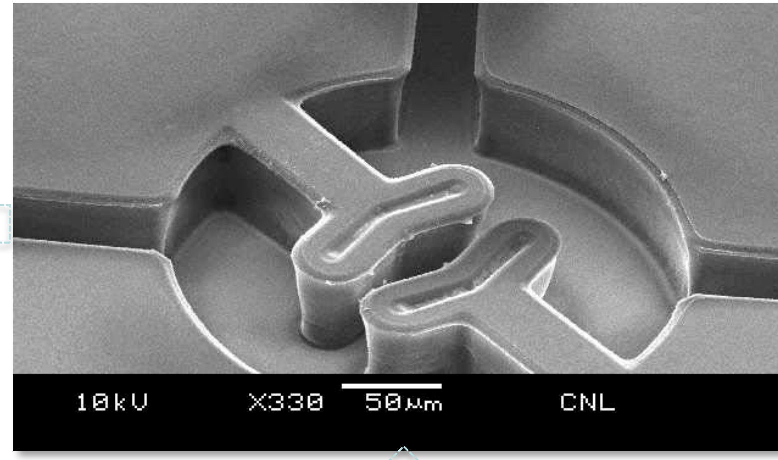
Wing with sensors and actuators

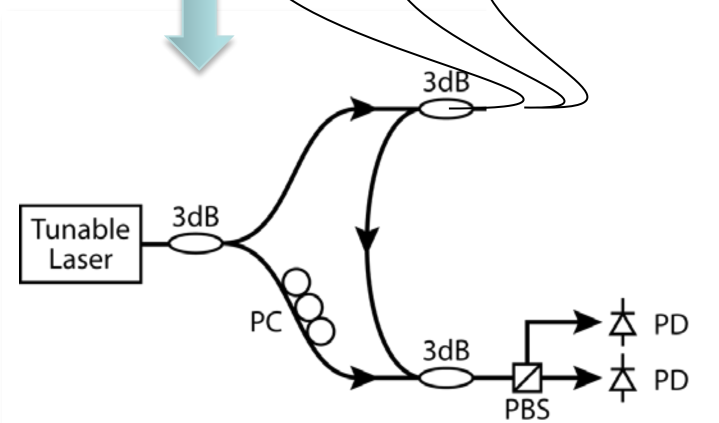


Amplifiers



Living neural network





Multi-channel sensor interrogation

Precision signal processing

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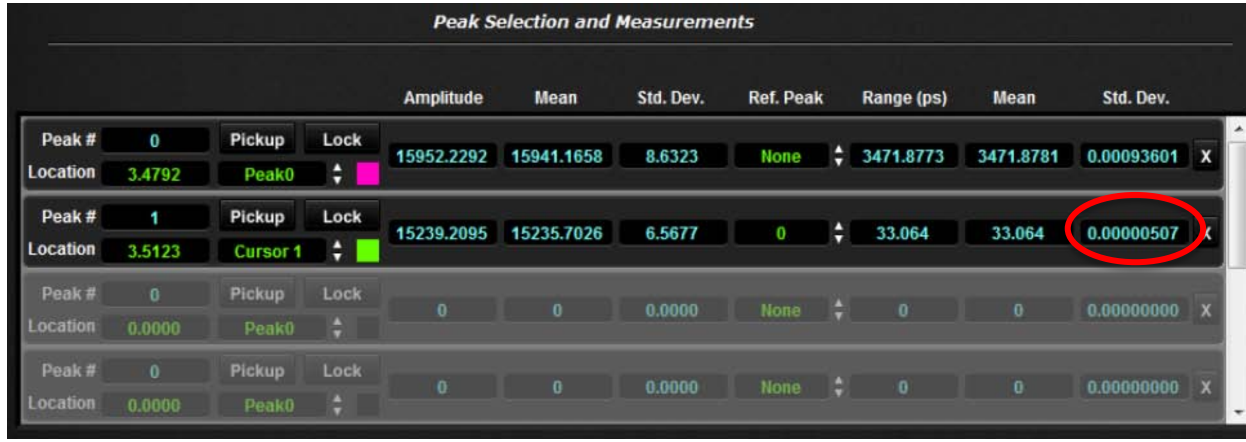
Precision interrogation results

Multiple (100's) sensor precision ranging supported by single network.

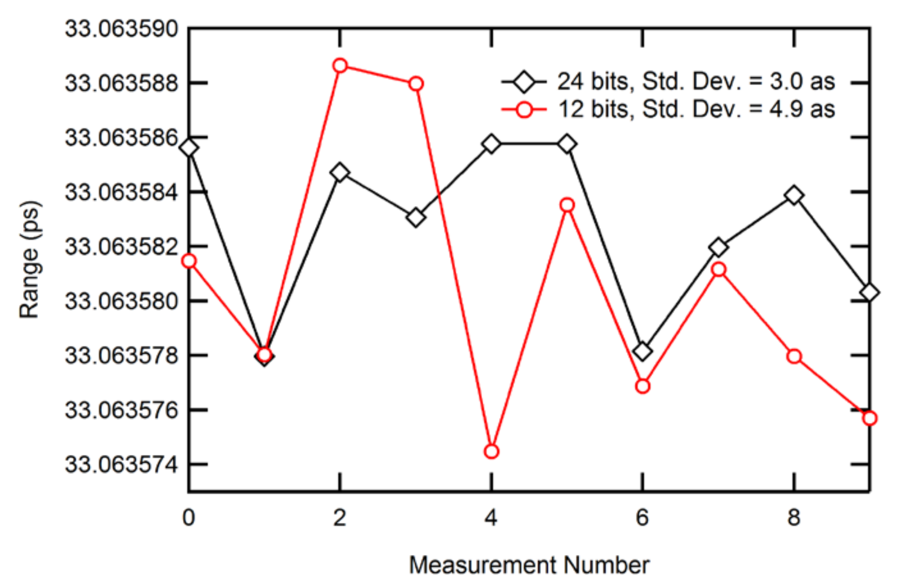


Peak Selection and Measurements

Peak #	Location		Amplitude	Mean	Std. Dev.	Ref. Peak	Range (ps)	Mean	Std. Dev.
0	3.4792	Peak0	15952.2292	15941.1658	8.6323	None	3471.8773	3471.8781	0.00093601
1	3.5123	Cursor 1	15239.2095	15235.7026	6.5677	0	33.064	33.064	0.00000507
0	0.0000	Peak0	0	0	0.0000	None	0	0	0.00000000
0	0.0000	Peak0	0	0	0.0000	None	0	0	0.00000000

Higher bit-depth DAQ

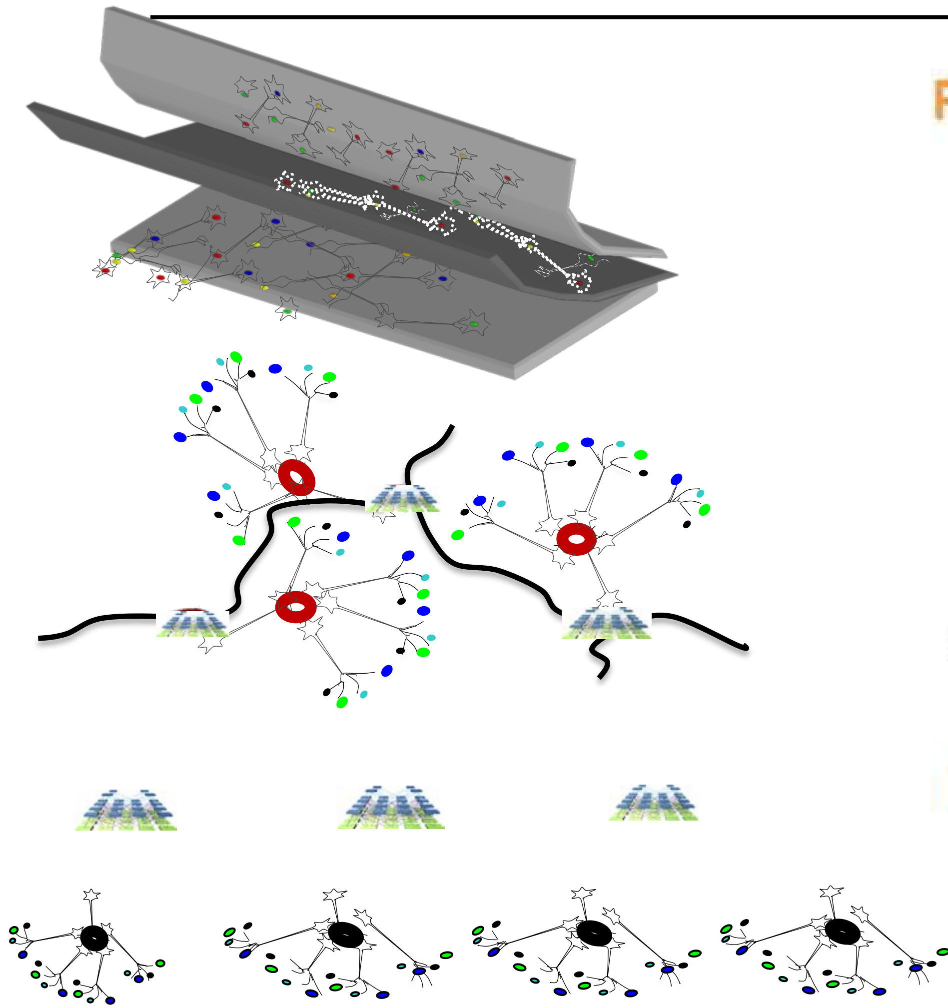
- New noise floor = 3.0 attoseconds
- Range uncertainty = ± 1.29 Angstroms in silicon

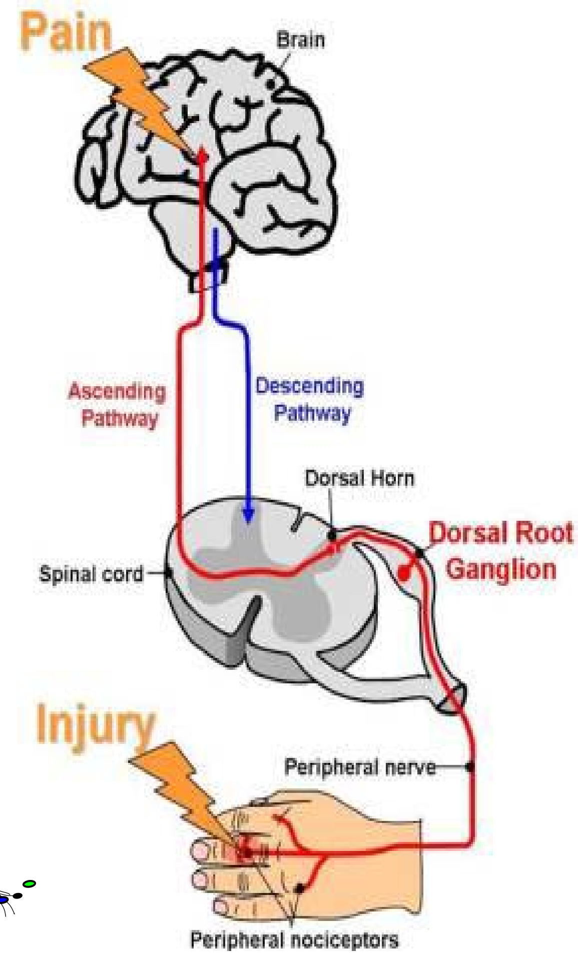


Neuron Circuits and Interface Electronics

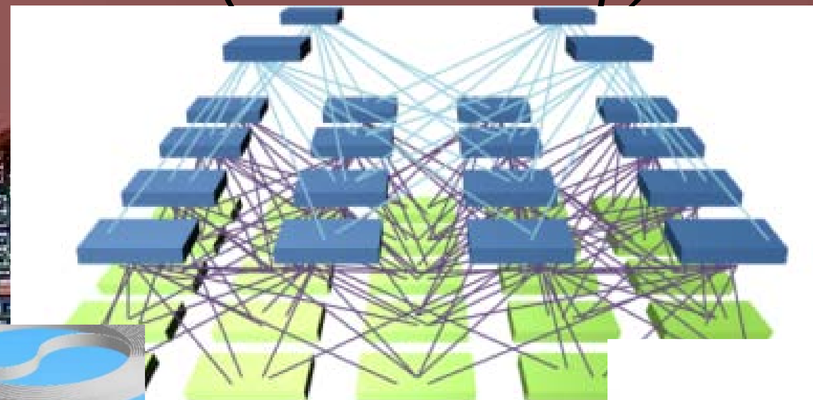
Chen – UCLA
Murmann – Stanford

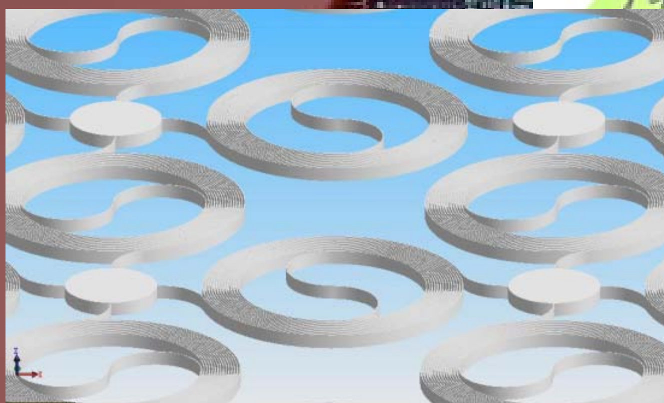
Material Development for Reasoning





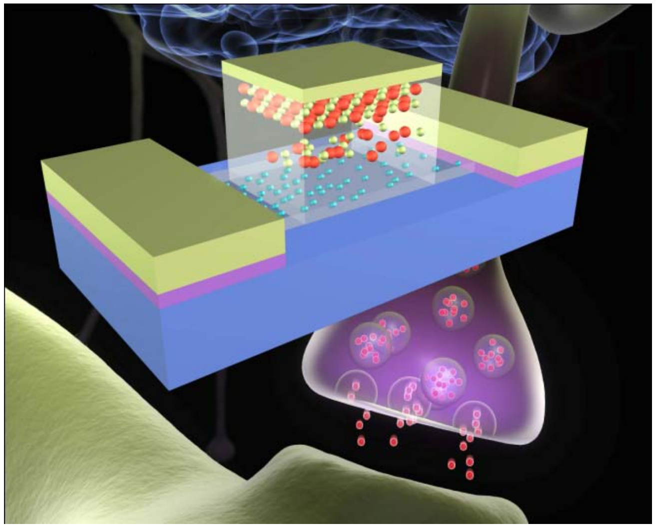
Neuron Circuits for Stretchable Network (Chen's Group)





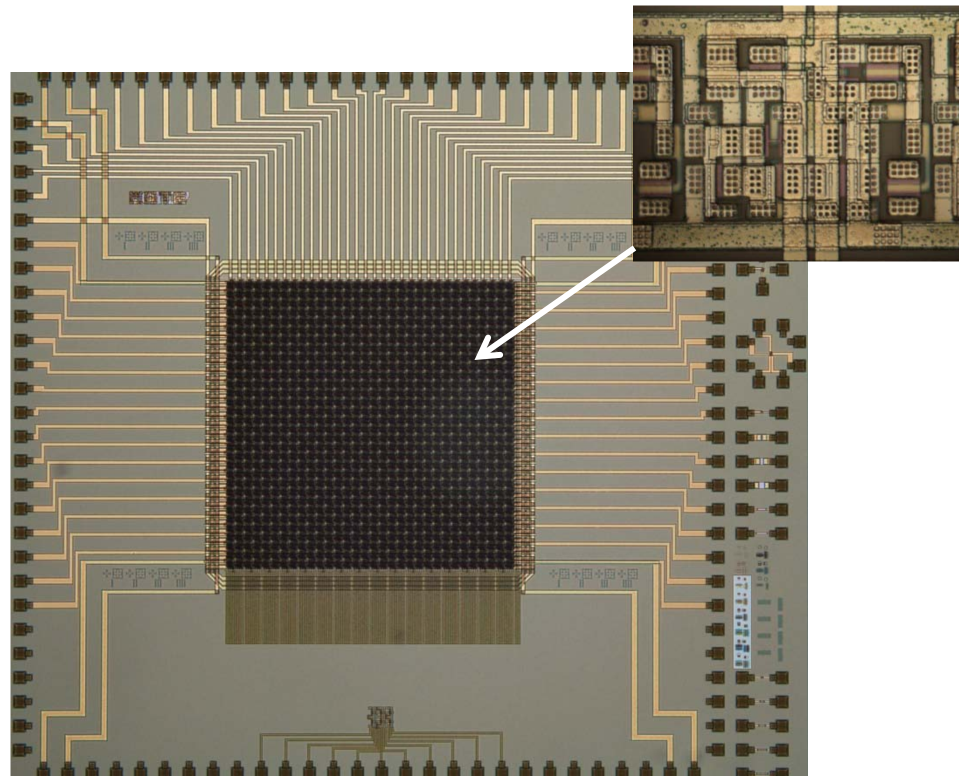
In this project, we plan to develop electronic neuron circuits based on carbon nanotube/polymer composites, and integrate the neuron circuits with sensing networks that can (1) promptly process a large amount of signals in parallel to recognize exogenous threats accurately and effectively, (2) implement real-time learning autonomously, and (3) provide dynamic prognosis for appropriate response for UAV.

Synaptic Transistor & Large-scale Neuron Circuit

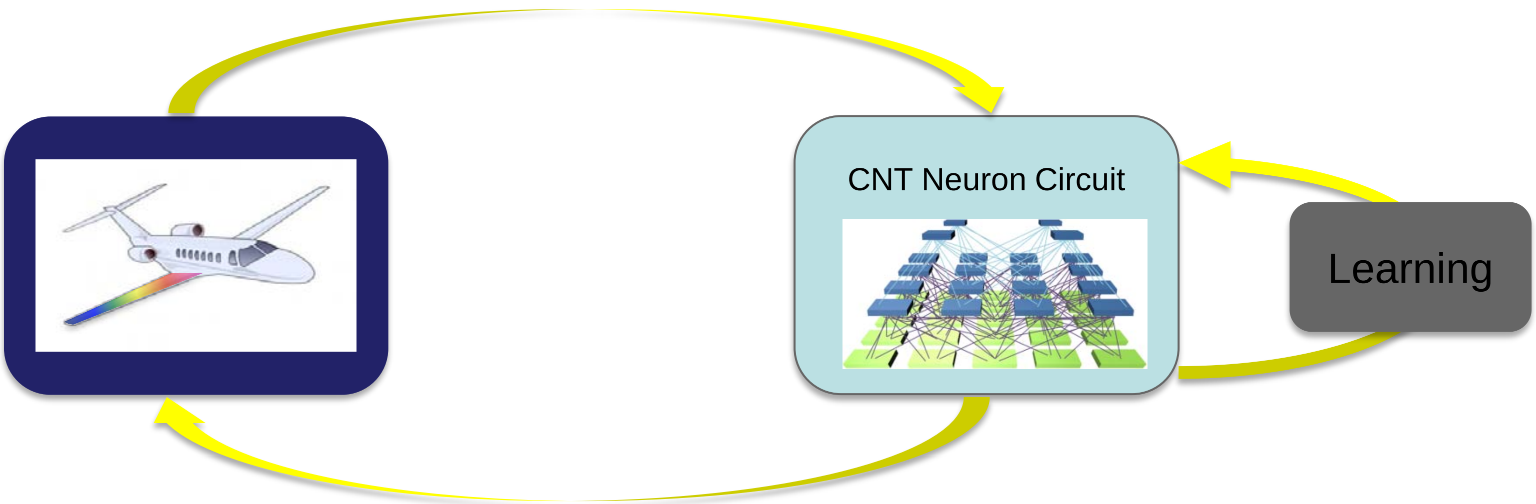


A synaptic transistor has been developed by integrating CNT and polymer materials to emulate biological synapse with spike signal processing, learning, and memory functions.

An image of a large scale neuron circuit by integrating 8192 synaptic transistors with Si MOS circuits with the functions of signal parallel processing, real-time pattern recognition, adaptive learning.



Dynamic Interaction between Neuron Circuit & System

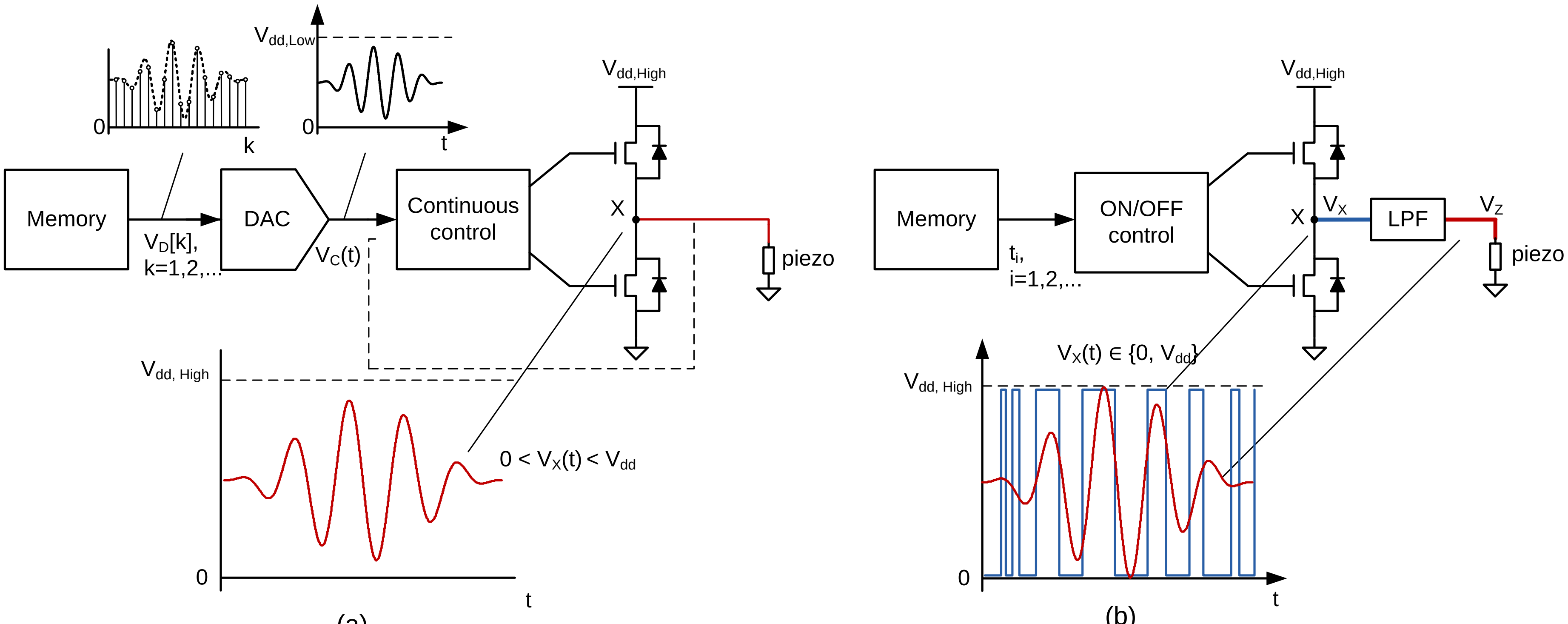


- ❖ Neurologically inspired theoretical models and architectures has been directly integrated and applied to establish the circuit architecture.
- ❖ The circuits have been integrated with the temperature sensing network developed at Prof. Chang's group at Stanford University.
- ❖ We will demonstrate (1) promptly process a large amount of signals in parallel to recognize exogenous threats accurately and effectively, (2) implement real-time learning autonomously, and (3) provide dynamic prognosis for appropriate response for UAV.

Interface Circuits for PZT Actuators (Murmann's Group)

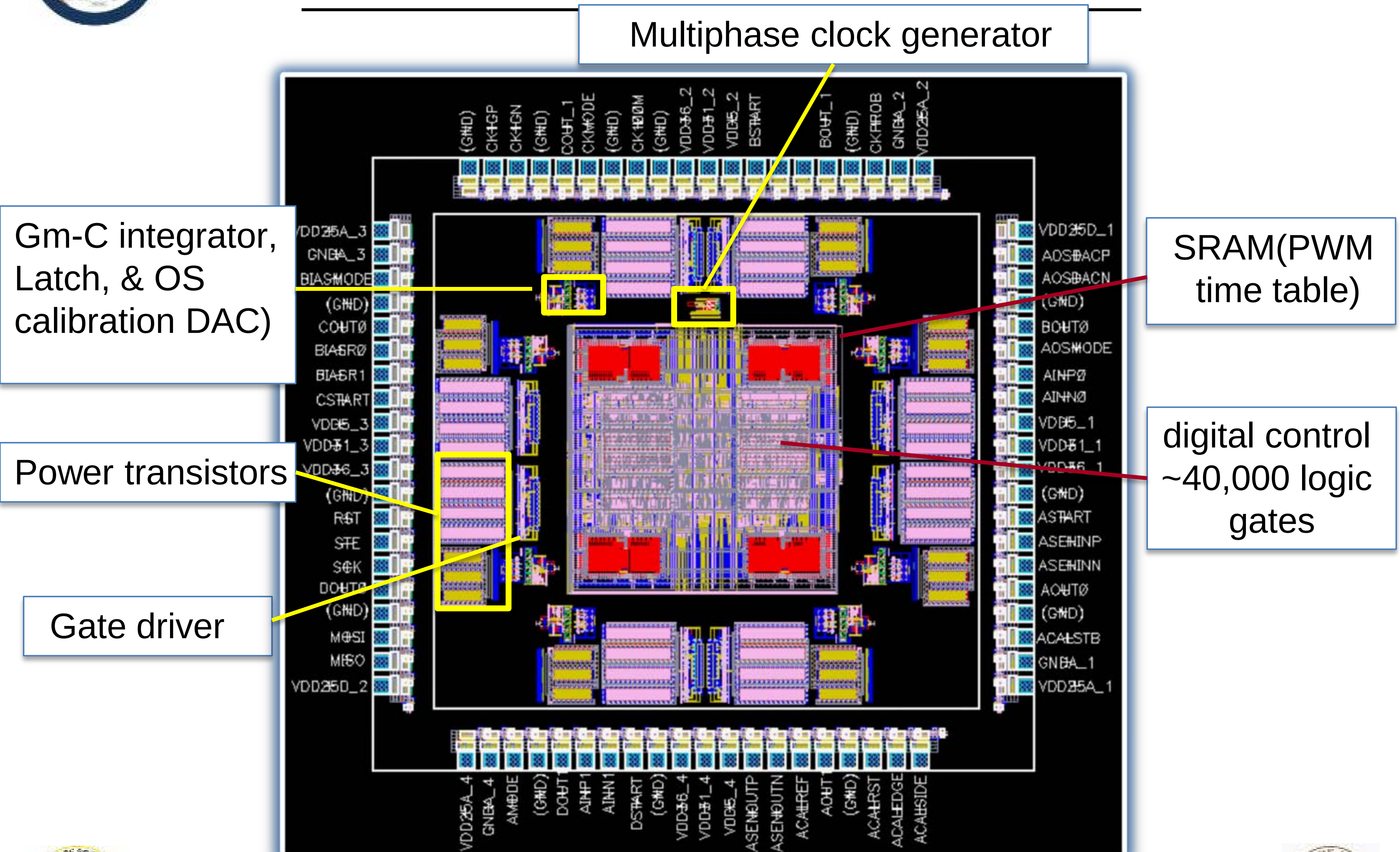
Densely Integrated Interface Circuits for State Sensing Network

- Using Pulse-Width-Modulation (PWM) to generate the excitation waveform
  - Render the waveform by a series of precisely timed binary pulses
  - High power efficiency: (a) is bounded by 78%; (b) is bounded by 100%



Structure of (a) a conventional piezo drive, and (b) a PWM piezo drive

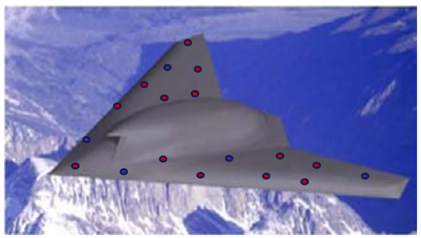
Chip layout (to be taped out on 8/19)



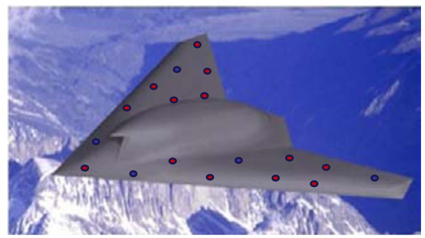
Potential Way

Baseline Generation

Generate large database of sensor responses for different structural states during training

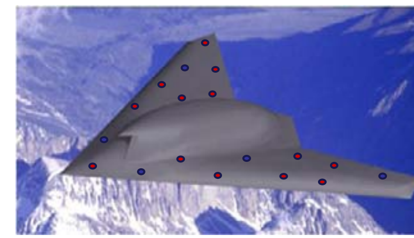


Record sensor responses at state ‘S_1’



Record sensor responses at state ‘S_2’

. . . .



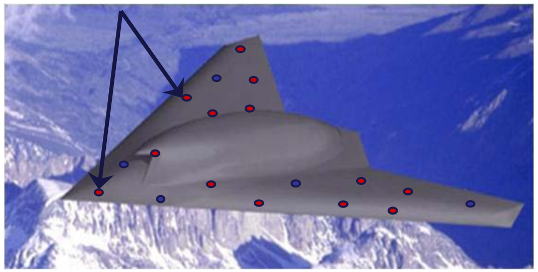
Record sensor responses at state ‘S_N’

- ***Enormous amount of effort & time consumption***
- ***Next to impossible to span entire range of environmental conditions and structural states***

The Proposed Approach

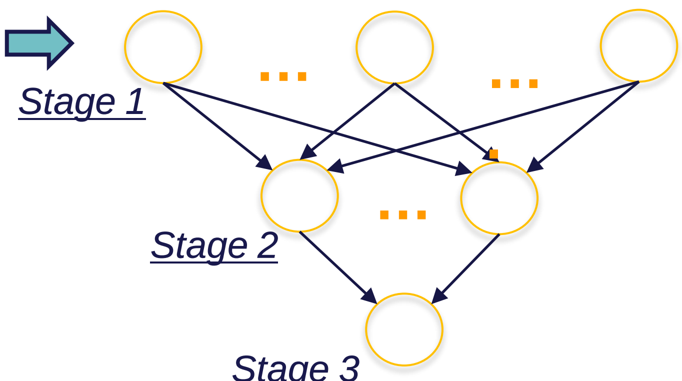
Data Driven Techniques ⟷ **Physics based Strategies**

Distributed Actuator/Sensors



Sensor signals on-the-fly

Unsupervised learning
(Neural-net Architecture)



Physics based compensation models

Supervised Learning

State Estimation

Structural changes

Damage types

Others …

Decision Management

Autonomous Guidance units

Modeling and Prognostics for Design and Validation

Ghosh – Johns Hopkins University
Chang – Stanford

Mechanical and Electromagnetic Coupling Modeling

Methods of Approach	Coupled Simulation	Multi-time Scaling

To develop an coupled multi-scale, multi-physics computational model and code for analysis of electromagnetic devices, e.g. sensors, antenna leading to design

Large Deformation Dynamic Response

Nonlinear hyper-elastic material

$$\underline{\underline{S}} = \lambda \cdot tr\left(\underline{\underline{E}}\right) + 2\mu \cdot \underline{\underline{E}}$$

Finite deformation problem

$$\int_{\Omega_o} \left(\delta \underline{u}^T \rho_o \underline{\ddot{u}}\right) dV + \int_{\Omega_o} \left(\delta \underline{\underline{F}}^T \cdot \underline{\underline{P}}\right) dV - \int_{\Omega_o} \left(\delta \underline{u}^T \rho_o \underline{b}\right) dV$$

$$= \int_{\partial\Omega_o} \delta \underline{u}^T \underline{\overline{t}}_o dS$$

Solve for

$$\underline{\dot{u}} \;\&\; \underline{u}$$

$\underline{\underline{S}}$: 2[nd]Piola-Kirchhoff Stress Tensor
E : Lagrangian Green Strain Tensor
$\underline{u}$: Displacement
λ, μ : Lame Constants

Transient Electromagnetic Field

Maxwell equations in total Lagrangian

$$\nabla \times (\underline{\boldsymbol{H}}(\underline{\boldsymbol{X}},t)) = \frac{\partial \underline{\boldsymbol{D}}(\underline{\boldsymbol{X}},t)}{\partial t} + \underline{\boldsymbol{J}}(\underline{\boldsymbol{X}},t)$$

Scalar and vector potential in reference configuration

$$\underline{\boldsymbol{B}} = \nabla \times \underline{\boldsymbol{A}} \qquad \underline{\boldsymbol{E}} = -\nabla\varphi - \underline{\dot{\boldsymbol{A}}}$$

$$\underline{\boldsymbol{H}}(\underline{\boldsymbol{X}},t) = \left[\begin{array}{l} \left(\varepsilon_0 J\left\{-\nabla\Phi - \underline{\dot{A}} - (\underline{\underline{F}}^{-1} \bullet \underline{\dot{u}}) \times (\nabla \times \underline{A})\right\} \bullet \underline{\underline{C}}^{-1}\right) \times \left(\underline{\underline{F}}^{-1} \bullet \underline{\dot{u}}\right) \\ + \frac{1}{\mu_0 J}\left\{(\nabla \times \underline{A}) \bullet \underline{\underline{C}}\right\} \end{array}\right]$$

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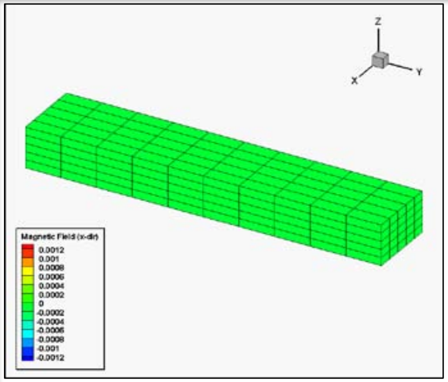
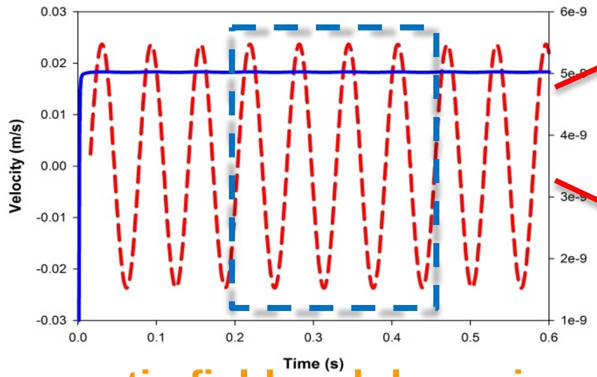
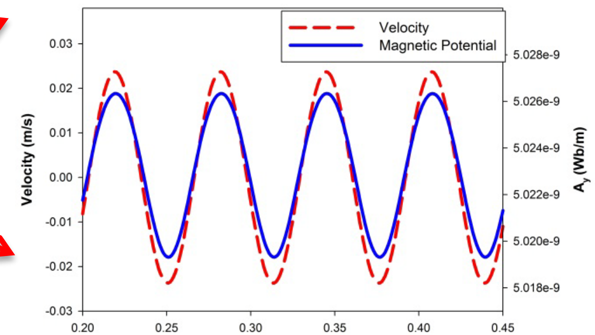
New York Institute of Technology

Coupling of Mechanical and Electromagnetic Field



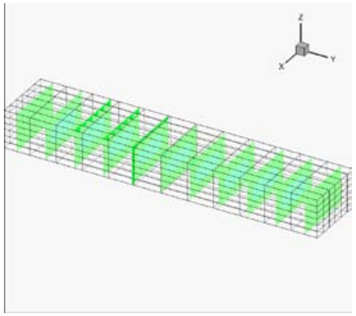




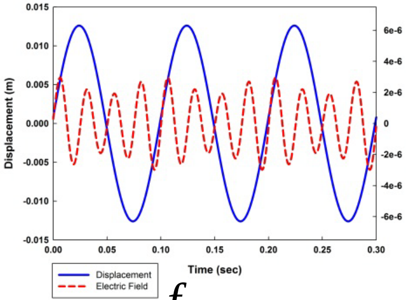
Coupled static electromagnetic field and dynamic mechanical field

1. Electromagnetic field is affected by the mechanical field
2. The magnetic potential is evolving by the velocity field other than the displacement field

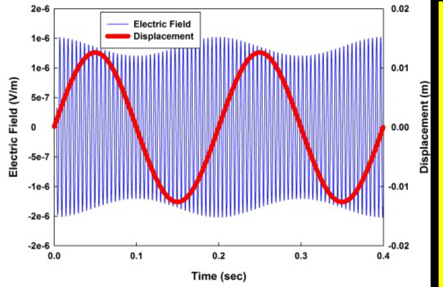
Coupled transient electromagnetic field and dynamic field



Electric Field



$$\frac{f_{em}}{f_{me}} = 4$$



$$\frac{f_{em}}{f_{me}} = 40$$

1. Electromagnetic field is evolving with the mechanical field
2. Frequency difference brings in significant computational expense

Multi-physics Spectral Element Method (Chang's Group)

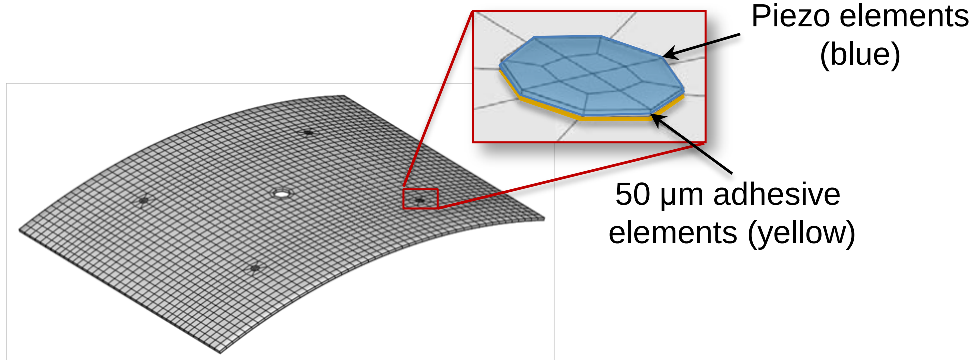
Efficient multi-physics computation tool for modeling ultrasonic waves

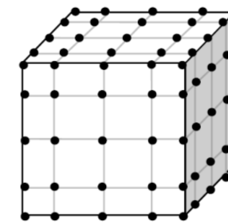
Equations of Motion

$$\sigma_{ij,j} + f_i = \rho \ddot{u}_i$$

Gauss's Law for Electricity

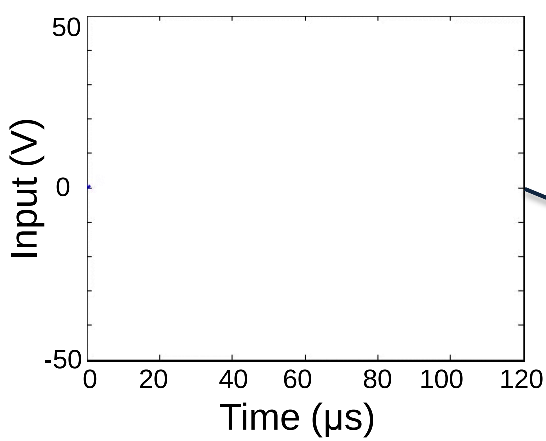
$$D_{i,i} = 0$$



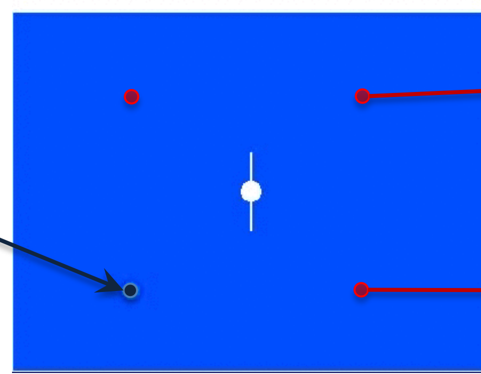


Solid Spectral element

Voltage Input to Piezo Actuator

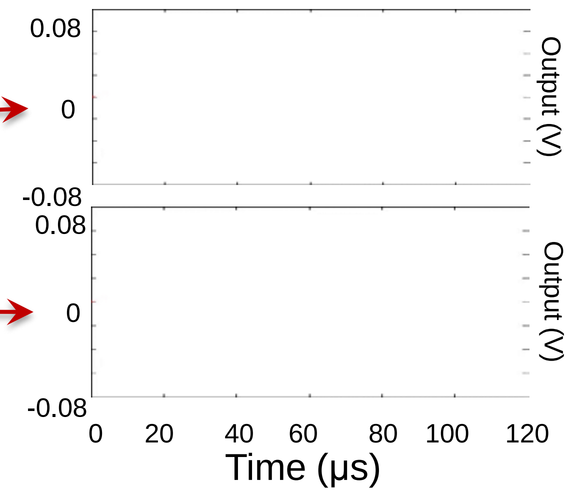


Induced Ultrasonic Stress Waves and wave-crack interaction



Aluminum plate with 20 mm cracks

Voltage Output at Piezo Sensor



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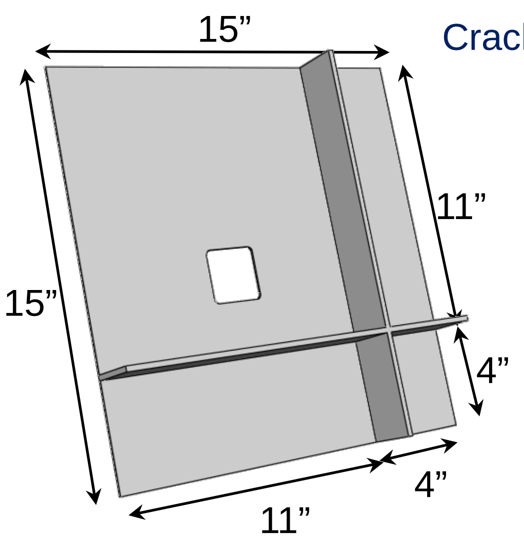
Design of Piezoelectric Sensor Network

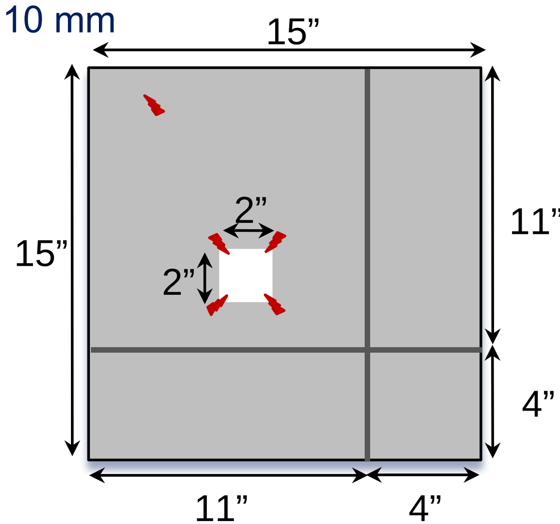
- PESEA : accurate simulations for a complex structure
- Genetic algorithm: 100% damage detectability with minimum number of Piezo actuators and sensors

Integration of PESEA and GA-based Optimization

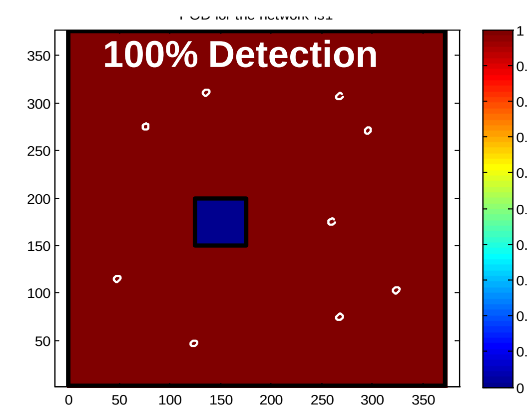
Given Structure ⇨ [PESEA ⇔ GA-based Optimization] ⇨ Optimal Sensor Layout



Crack ≥ 10 mm



Detection and Localization



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NYIT New York Institute of Technology
UBC

Diagnostics and State Awareness

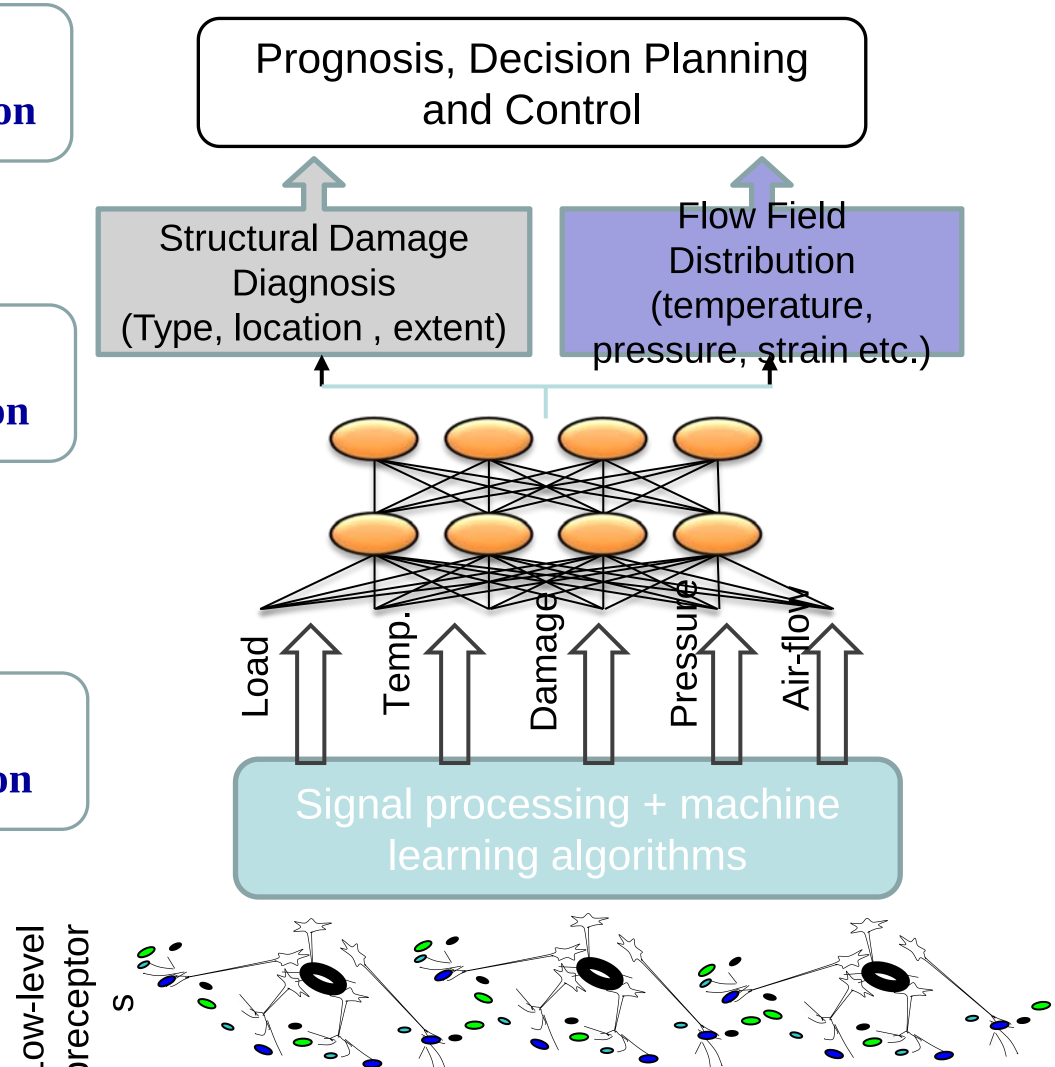
Chang, Ng – Stanford
Shoureshi – NYIT

Sensor Data Processing

STAGE 3
Autonomous decision

STAGE 2
State Quantification

STAGE 1
State Classification



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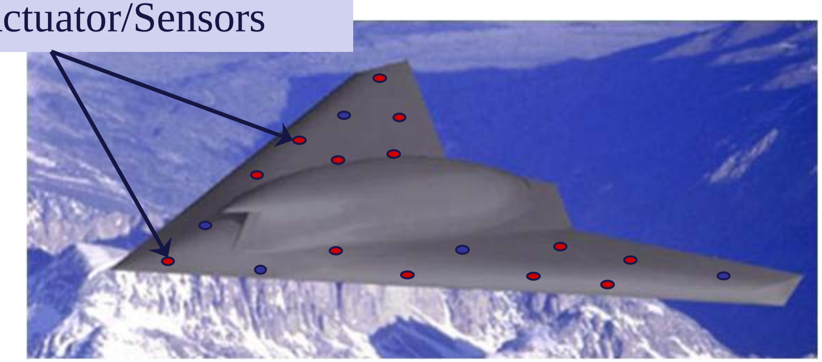
Motivation

<u>*Sensor Data Interpretation in Real-time*</u>

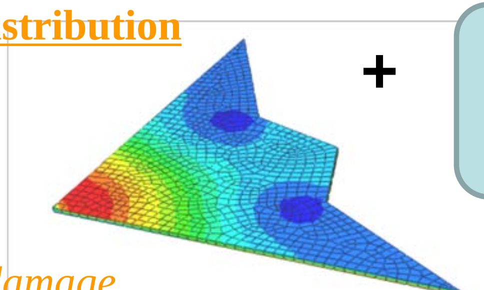
Distributed Actuator/Sensors



Sensor Response: $S_i = f\,(\Delta\text{load}, \Delta\text{temp.}, \text{localized damage}, \Delta\text{BCs}, \Delta\text{sensor state} \ldots)$

State field distribution

-Temperature
-Pressure
- Air-flow
- Strain
- Structural damage



+

Environmental Effects
Ambient temperature, humidity. moisture…..

=

Corrupted Sensor Data

How to accurately assess the structural state information from a network of multi-functional sensors?

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New York Institute of Technology

State Classification: Designed features

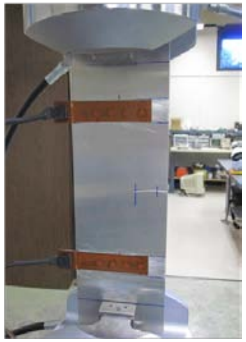
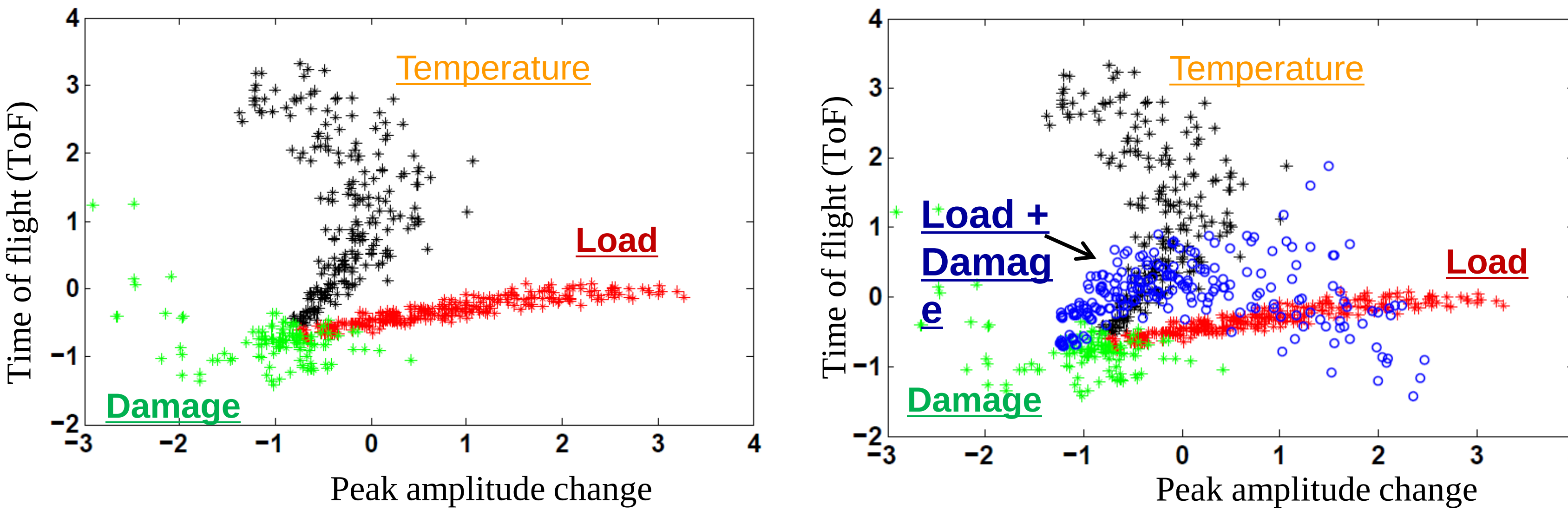


Table: Sensor signal measurements under simulated environmental conditions

Number of Samples	Temperature Range	Load Range	Simulated Damage
4 coupons	30°C - 95°C	0kips – 5kips	0.25” - 1.5” Notch at the edge
4 sensing paths per actuator; Paths per measurement = 16; # of measurements = 1136			

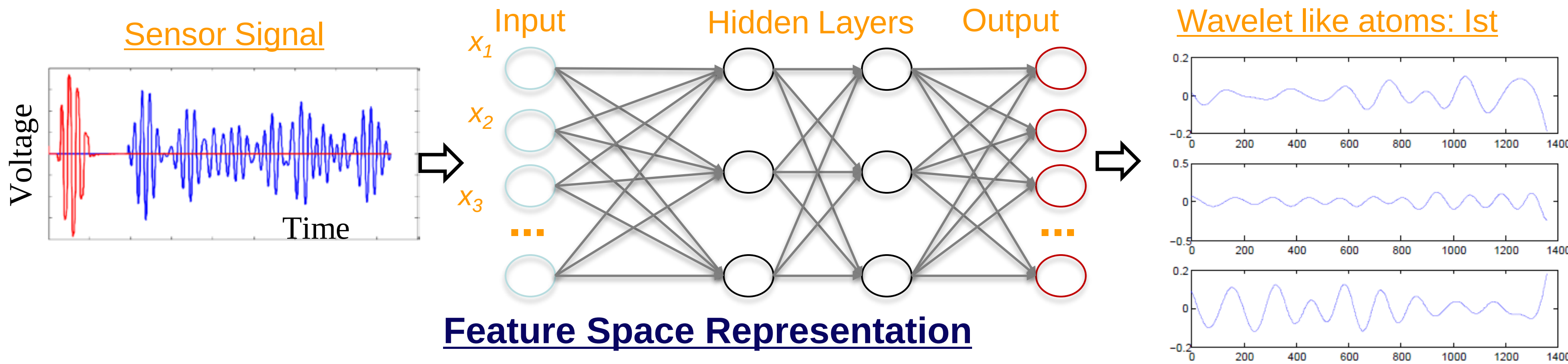
Feature Space Representation



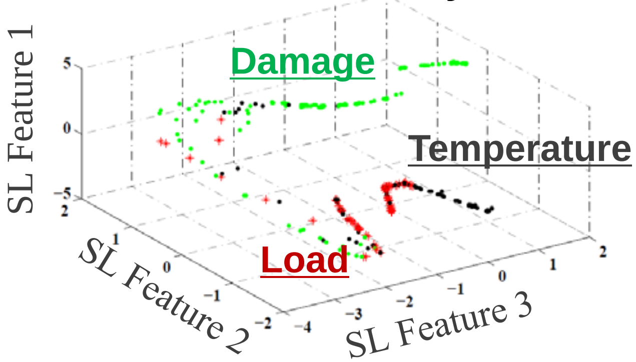
Difficult to identify true state under combined action of load and damage; State Classification Accuracy (logistic regression) < 30%

State Classification: Self-Learned Features

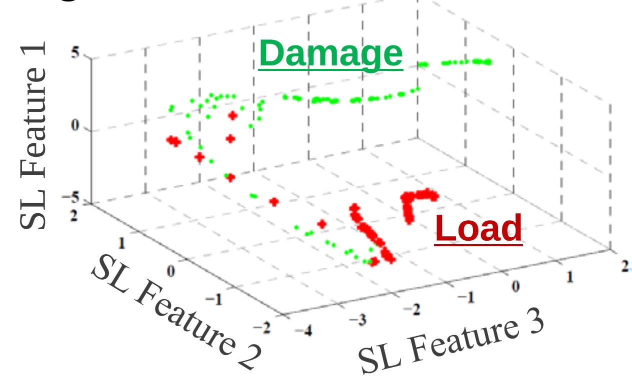
Unsupervised Features Learning: Neural-net based 'Sparse Auto-Encoders'



Physical Model + Self-Learning Strategies



Physics-based Compensation Model



Self-learned features outperform the self-designed features for state classification

Scaling Feature Learning

- Current system scales better; but still some distance to go for a full-scale application.

Prior art

10^4 neurons

1M parameters
50,000 examples

Our previous system

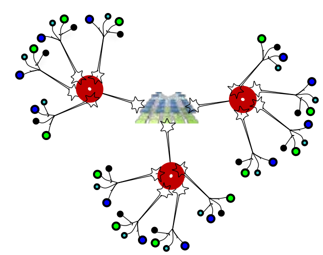
10^6 neurons

> 2M parameters
50,000 examples

→ **Local receptive fields, weight-tying**

Fly-by-feel aircraft

Goal: 10^7 to 10^8 neurons



100M parameters
>10M examples

Approach

- Fold prior MURI work into extremely large-scale system:
  - Scalable K-means learnir **66M parameters**
  - Online training **57M examples.**
  - Locally connected neurons.
  - ***New invariant-feature learning approach.***

Proof-of-concept

- Applied to unlabeled image data.

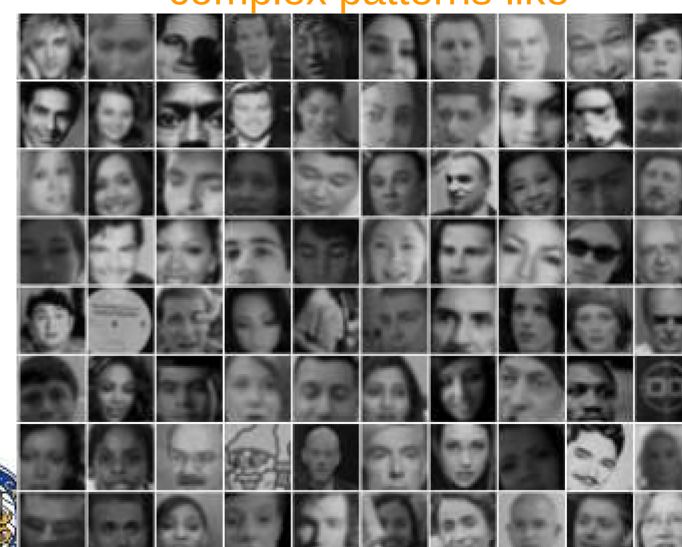
  66M parameters, 57M data points.

  (1000x more data than standard benchmarks.)

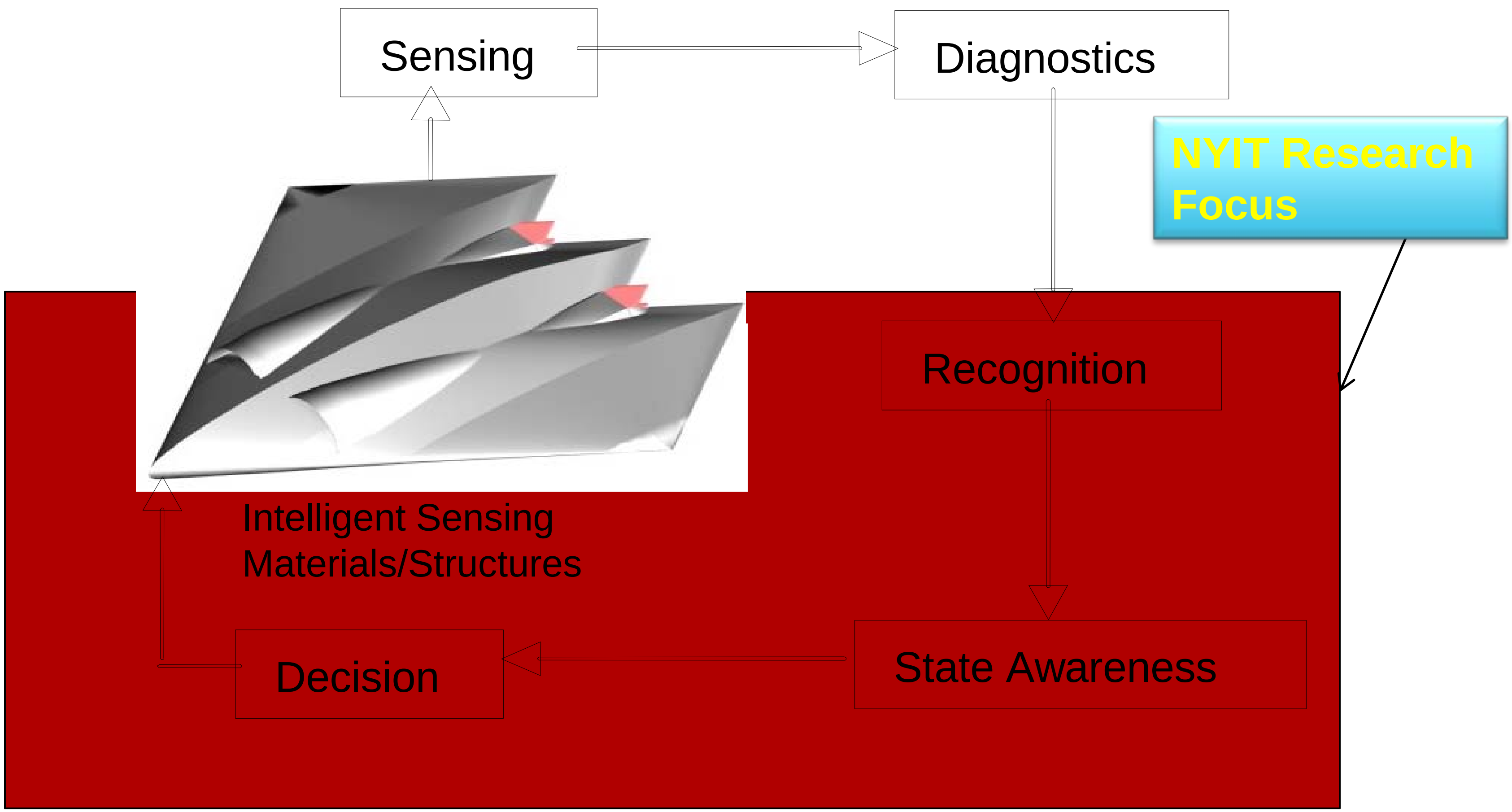
1.4 million images.

57 million patches.

Single neuron selects complex patterns like



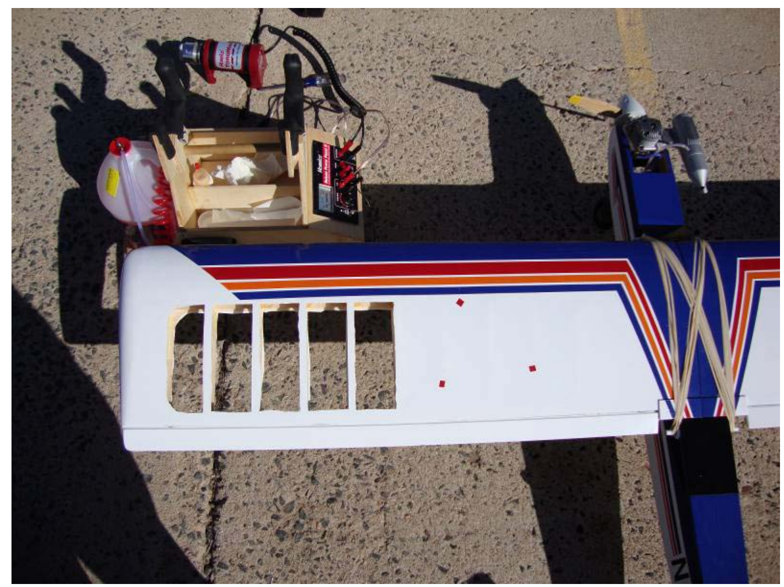
From Sensing to Decision Making (Shoureshi’s Group)



Goals

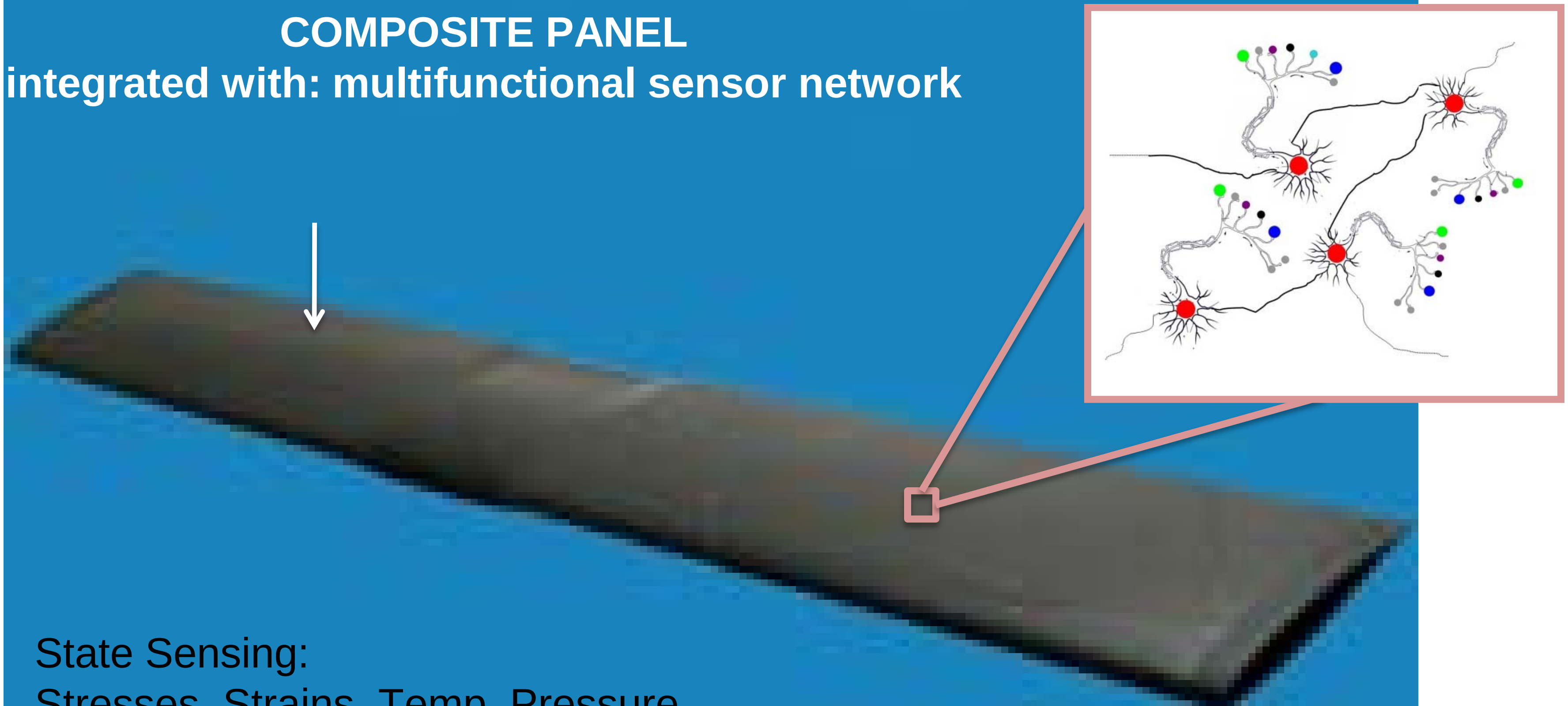
– To develop an analytical technique for observability and controllability of large-scale, dynamic systems
– To develop a bio-inspired data/information architecture for feature-based global diagnostics of a large-scale system
– To develop a bio-inspired, feature-based re-configurable control system to maintain vehicle functionality in the presence of system failures
– Design a testbed to assess MURI team research results

Controller and Diagnostics Testbed



Prototype I

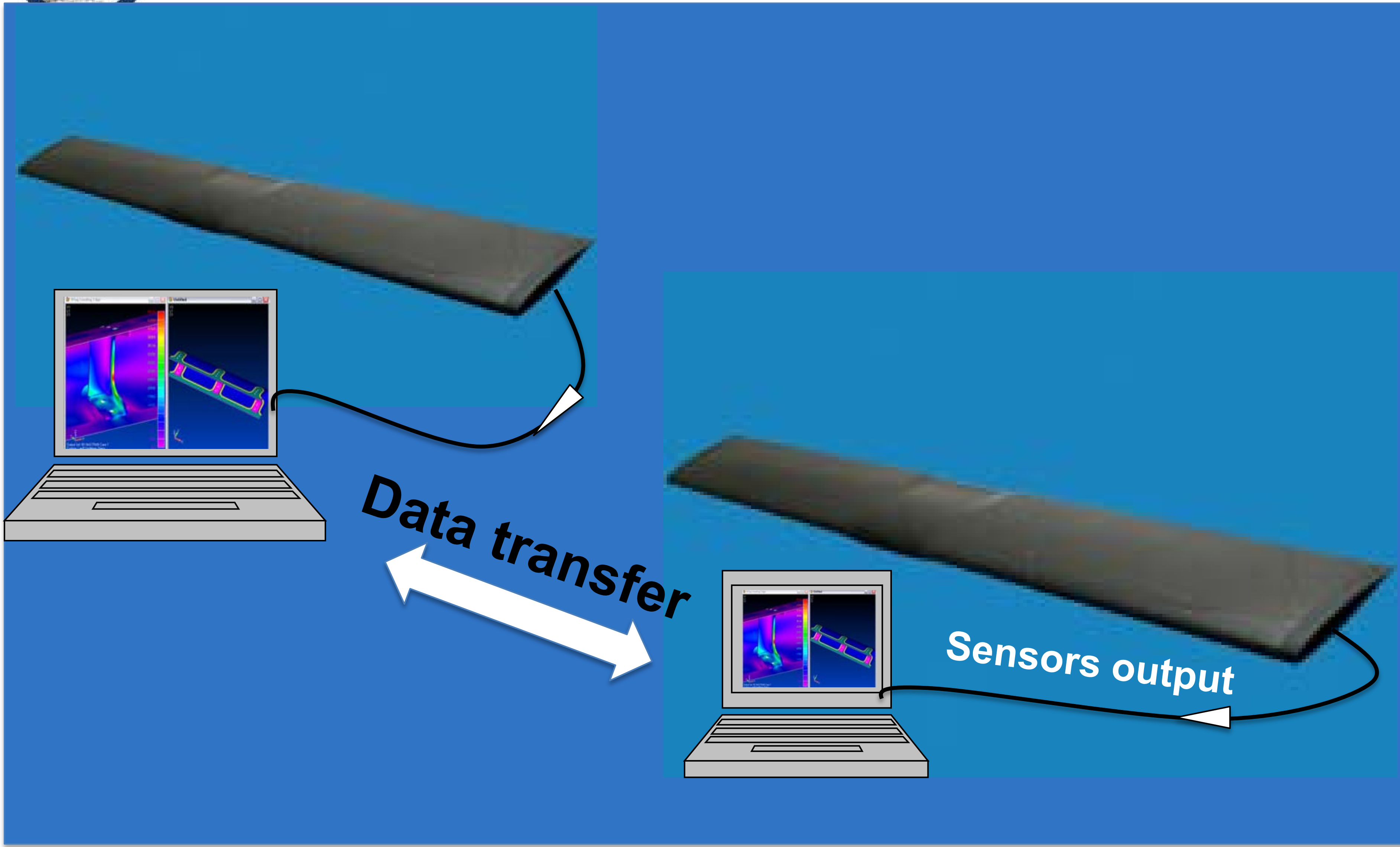
COMPOSITE PANEL
integrated with: multifunctional sensor network



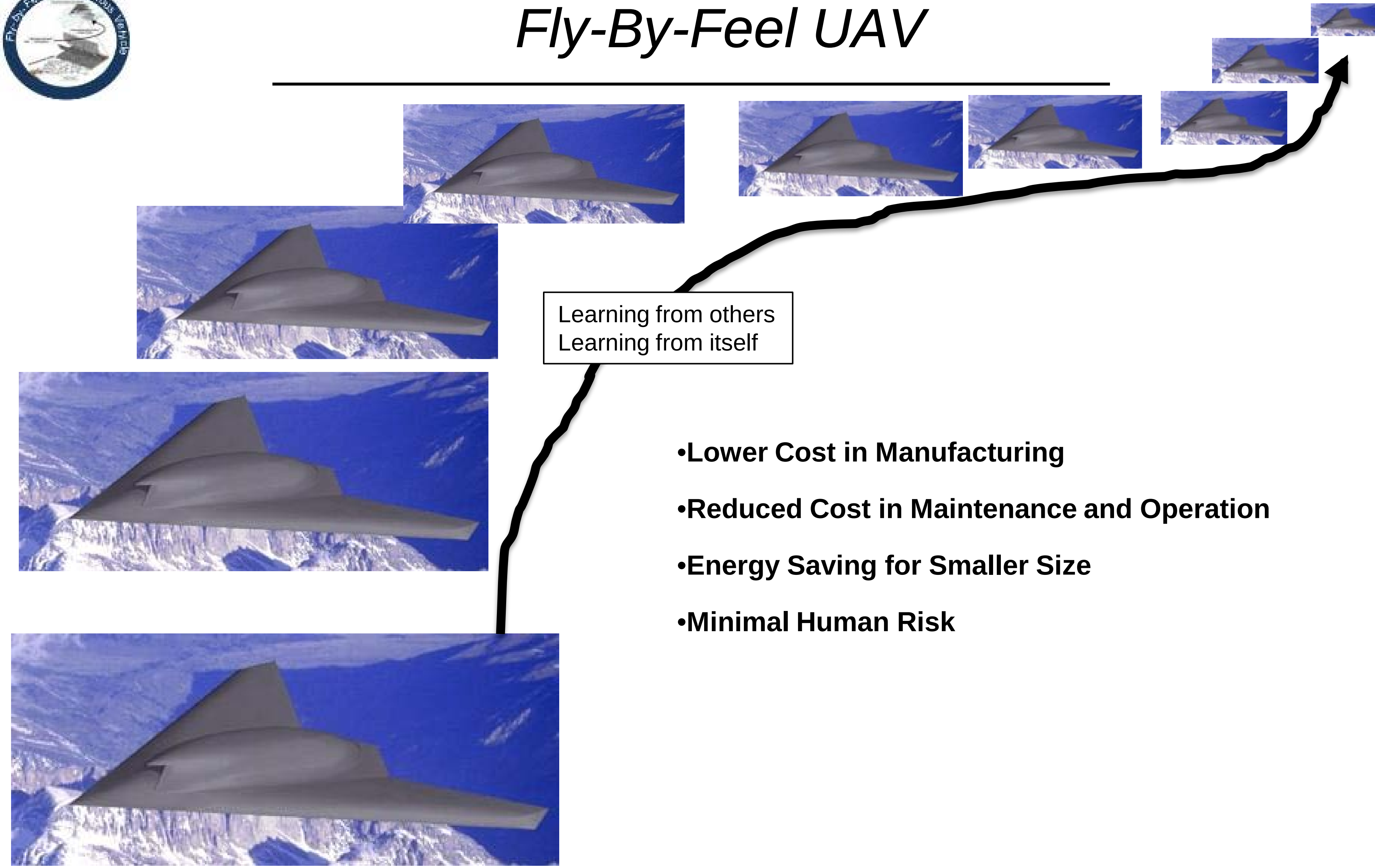
State Sensing:
Stresses, Strains, Temp, Pressure,
Loads, Damage/Failure, Remote Threats, etc.

New York Institute of Technology

Prototype II: Learning without Training



Fly-By-Feel UAV

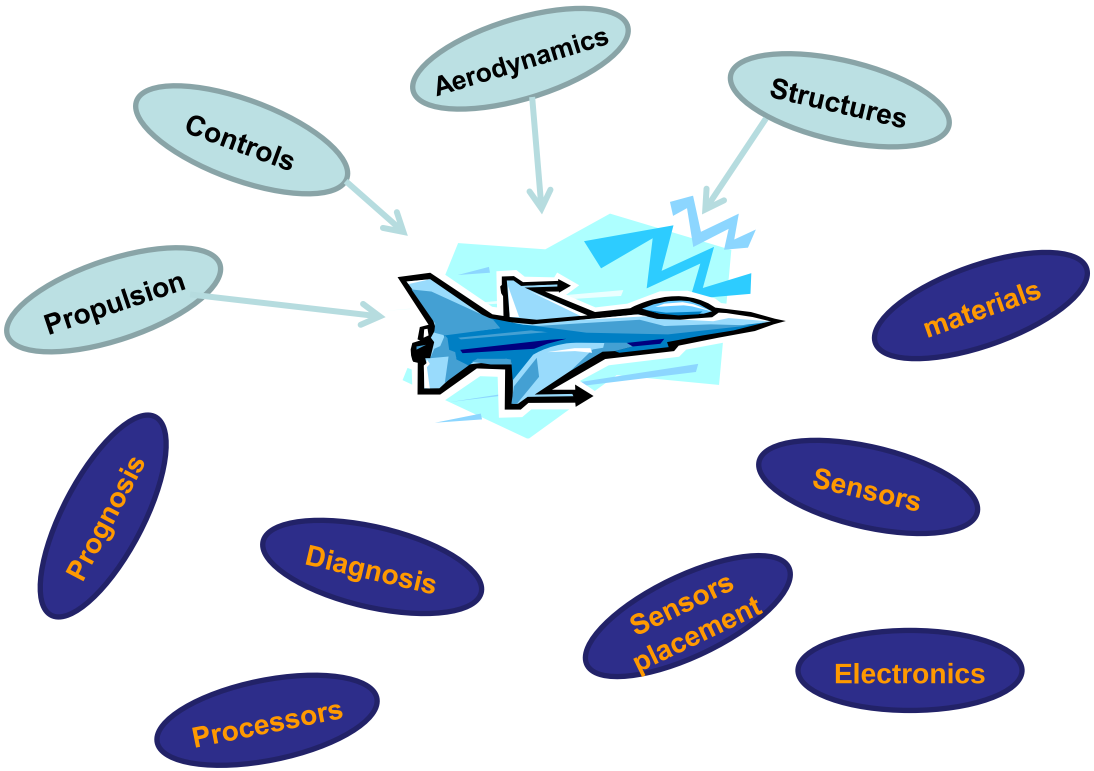


- **Lower Cost in Manufacturing**
- **Reduced Cost in Maintenance and Operation**
- **Energy Saving for Smaller Size**
- **Minimal Human Risk**

Traditional design of structures is divided into a few disciplines

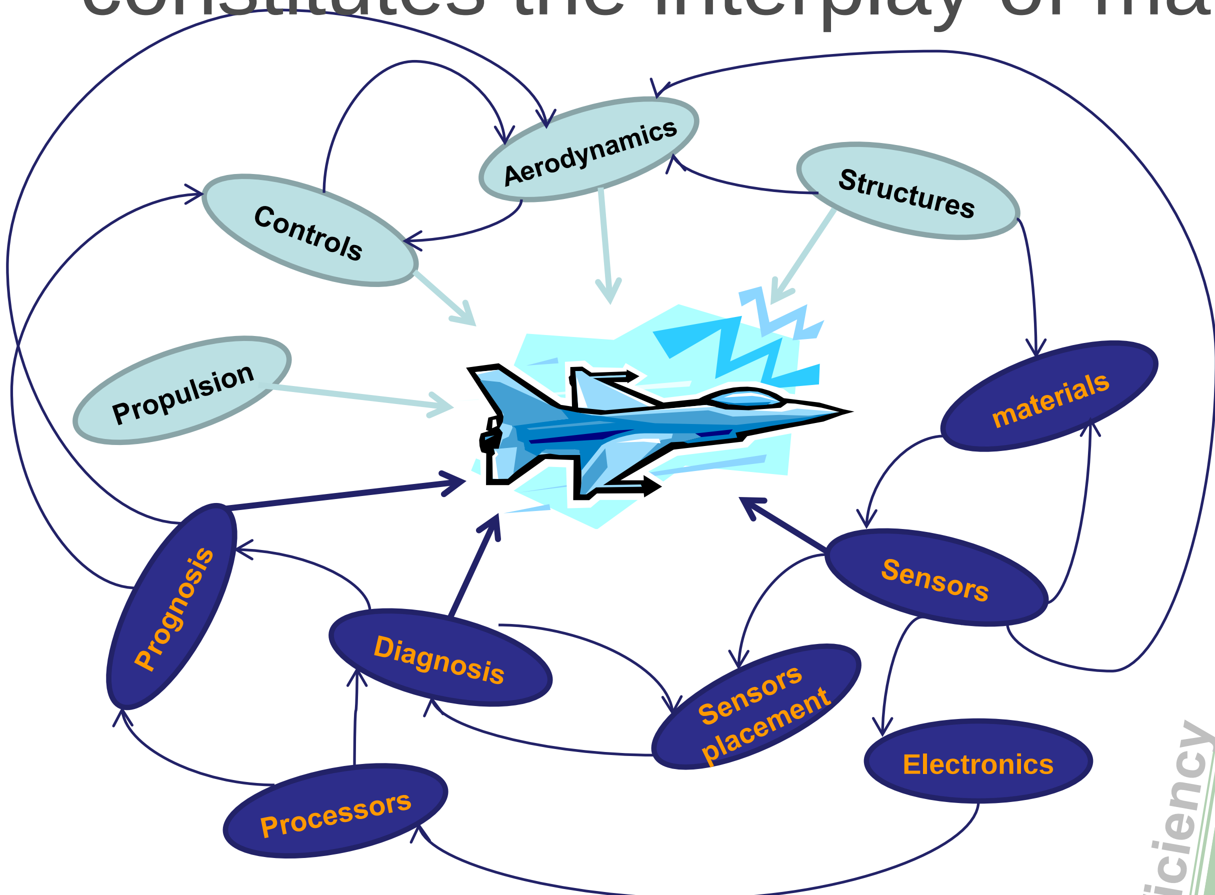
Resulting in
→overdesigned structures
→heavy airplanes
→time consuming inspections
→inappropriate maintenance schedules
→catastrophes

Technologies developed during MURI



Requires ***re-thinking*** the traditional design strategies

Intelligent design constitutes the interplay of many



… but will result in

Concept: "Build confidence on design"

Controls

Aerodynamics

Propulsion

Structures

Confidence on design and performance

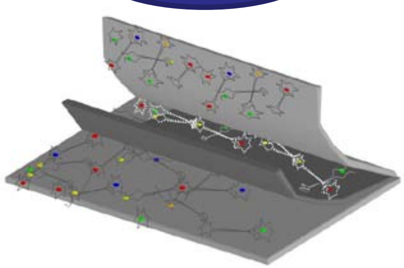
materials

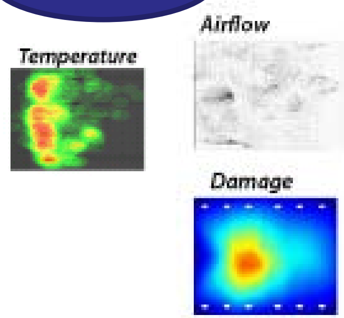
Sensors

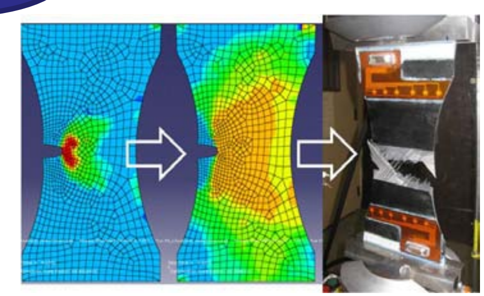
Built-in intelligence

Diagnosis

Prognosis







Minimize uncertainties
→weight Saving

Life cycle management

Manufacturing

Transportation

Assembly

Service

Maintenance & Repair